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Analysis of Smuggler Movement on Multiple Transportation Networks

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Analysis of Smuggler Movement on Multiple Transportation Networks

by

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Report

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Abstract

Analysis of Smuggler Movement on Multiple Transportation Networks

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The University of Texas at Austin, 2011

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We analyze an interdiction problem in which a nuclear-material smuggler can traverse multiple transportation networks, wherein each edge has an indigenous probability of evasion. Our objective is to determine the optimal locations of a limited number of radiation detectors at United States ports of entry across multiple networks (maritime, road and rail) so as to minimize the smuggler's total probability of evasion, from origin to destination. We choose geographically diverse potential origins and give the smuggler freedom to move across and between transportation networks. Further, we consider two different models of smuggler behavior in this context. Our analysis aims to provide a complete prioritization and picture of the threat at all ports of entry, leading to insight into good practical locations for detectors.

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1. Introduction and motivation

Nuclear weapons pose a serious threat to the safety and security of the United States and its people. The dissolution of the Soviet Union resulted in a lot of excess nuclear material, intended for the manufacture of nuclear weapons, to be left in unsecured or vulnerable locations. Even nuclear material not enriched to weapons-grade levels can be combined with conventional explosives to make a so-called “dirty bomb”, which uses the explosives to disperse the radioactive plutonium or uranium. Other radioactive material can also be used in a dirty bomb. These weapons have the potential to cause catastrophic damage on a wide scale, especially if detonated in a densely populated area. Therefore, the risk of such materials getting into the United States is a serious concern for the Department of Homeland Security and other law enforcement agencies. This article is concerned with mitigating the risk posed by smugglers attempting to introduce potentially dangerous nuclear materials into the country. To reduce the risk of a smuggler reaching their target in the United States, we install detectors sensitive to nuclear material at ports of entry into the country. We assume that detectors can only be placed at border ports of entry. The finite number of U.S. ports of entry limits the number of potential routes into the United States, thus creating useful security bottlenecks for screening incoming traffic. By placing detectors at ports of entry we take advantage of these existing bottlenecks and ensure that all incoming traffic is screened if detectors are installed at all ports of entry. Furthermore, we achieve this with fewer resources than it would take to do so by encircling every potential target in the United States with detectors, for example. Since simultaneously upgrading security at all ports of entry is prohibitively expensive, we need to know how to best allocate limited numbers of radiation detectors so as to minimize the probability of a smuggler successfully bringing dangerous nuclear materials into the U.S.

The problem of how to best interdict smugglers and protect the United States from such a threat is broad, and the problem allows for a variety of potential approaches and areas of research. Although much thought and resources have been put toward developing more sophisticated and reliable radiation detectors, the problem of where to allocate and install these detectors so as to minimize threat remains relatively unexplored. The goal of this article is to give some insight into and answers to this facet of the nuclear materials smuggler problem.

2. Literature review

Network interdiction models have been studied extensively in the past. In one of the earliest references, Fulkerson and Harding [5] discuss the problem of maximizing an adversary's shortest path. Reed [13] and Brown et al. [2] examine the problem of maximizing the longest path in the Program Evaluation and Review Technique (PERT) network of an adversary, thereby maximizing the time to project completion. In the continuous case, this is done by lengthening an arc and thus increasing the length of the adversary's preferred path. In the discrete version, maximizing the shortest path involves removing an interdicted arc from the network, or discretely lengthening it, thereby forcing the adversary to change their path selection. In both cases, the interdictor faces a budget constraint, representing available resources. In the case where that budget constraint is one of cardinality (i.e., the interdictor can remove at most k arcs from the network), the problem is known as the k-most-vital-arcs problem. This is presented by Corley and Sha [3] and Malik et al. [7]. All of these articles present deterministic models of network interdiction, where arc lengths are known with certainty, as the effects of removing or lengthening an arc. Stochastic network interdiction models have been discussed, however, by Hemmecke et al. [6] and Bailey et al. [1], among others.

3. Model

The problem in question is a stochastic network interdiction model. We are dealing with an intelligent, informed smuggler who travels over a given transportation network, choosing the path from origin to destination which maximizes his evasion probability. Prior to the smuggler selecting this path, the interdictor installs radiation detectors to minimize the smuggler's evasion probability. Since we limit potential detector locations to ports of entry into the United States, with all origins outside the border and all destinations within the country, the model is defined on a bipartite network. The problem is stochastic in nature because the interdictor only knows the smuggler's origin and destination through a probability distribution.

3.1. Model formulation

Ours is a special case of a basic interdiction model, which is described below.

3.1.1. Interdiction model

$k \in K$	ports of entry
$\omega \in \Omega$	smuggler type
P^{ω}	probability of threat scenario ω
c_k	cost of installing a detector at k
b	installation budget
x_k	1 if detector is installed at k; 0 otherwise

$$\min_{x} \sum_{\omega \in \Omega} P^{\omega} h(x, \omega)$$
$$\text{s.t.} \sum_{k \in K} c_k x_k \leq b$$
$$x_k \in \{0,1\}, \qquad k \in K$$

where $h(x, \omega)$ is the evasion probability for smuggler ω.

For every budget value b, the objective function of this model has us selecting the set of ports of entry at which to install detectors (k for which $x_k = 1$) such that we minimize the sum of the evasion probabilities $h(x, \omega)$ for all smugglers $\omega \in \Omega$ (defined by an origin-destination pair), each weighted by the probability of seeing such a smuggler, denoted by P^{ω}. This is done subject to the constraint that the total cost of installing all detectors (the sum of costs c_k over all k for which $x_k = 1$) is less than or equal to the budget value b. In our model we assume that the cost c_k of installing a detector at port of entry (POE) k is equal for all $k \in K$, transforming the budget constraint into a cardinality constraint. The evasion probabilities $h(x, \omega)$ are discussed in more detail below.

3.1.2. Evasive and volume smugglers

We consider two basic strategies that smugglers might adopt in their efforts to cross the border undetected. The first of these is given by the evasive smuggler (developed in Morton et al. [8]). This smuggler represents the worst-case smuggler behavior from the interdictor's point of view. Evasive smugglers have perfect information on detector locations and the evasion probabilities of every path they could take. They optimize over all possible paths from origin to destination, picking the one that maximizes their evasion probability.

The competing strategy is that of the volume smuggler. This smuggler adopts a "needle in haystack" approach to getting through the border; they believe they are most likely to go by undetected through the POE that sees the most traffic. For the volume smuggler, the probability of selecting any POE is directly proportional to the volume of traffic that goes through that port. Thus the best strategy for thwarting the volume smuggler is to screen as much of the traffic coming into the country as possible.

One way to approach both of these threats is to express them as separate objective functions. In the case of the evasive smuggler, the objective is to minimize the smuggler's maximum evasion probability; that is to say, we need to make the best possible path this smuggler can take as unfavorable for the smuggler as possible. With the volume smuggler on the other hand, our objective is coverage: we want to screen as much traffic as possible to minimize this smuggler's evasion probability. This is how we consider these different scenarios from here on in this article. We use the parameter λ to represent the weight of the objective of thwarting the evasive smuggler as opposed to the volume smuggler. Thus, in the above formulation,

$$h(x, \omega) = \lambda * h_E(x, \omega) + (1 - \lambda) * h_V(x, \omega)$$

where $h_E(x,\omega)$ is the evasion probability of evasive smuggler ω given detector installation vector x, and $h_V(x, \omega)$ is the evasion probability for a volume smuggler given detector installation vector x. These two functions are defined in Section 3.2 below.

3.1.3. Probabilistic and adversarial smugglers

Beyond evasive and volume smugglers, we consider smuggler behavior in terms of how smugglers might pick their targets. The first of these is the probabilistic smuggler. In this case we have one smuggler equally likely to be leaving any of the given origins and having an equal probability of picking any destination. Thus the number of threat scenarios is equal to the number of origin-destination pairs, and each threat scenario is equally likely.

In the adversarial smuggler scenario, we again have a smuggler who is equally likely to be leaving any of the given origins, but instead of picking any destination with equal probability, the smuggler targets the destination which can be reached with the highest evasion probability from his chosen origin. The adversarial smuggler optimizes not only over routes, but also over destinations. Under these conditions, the number of threat scenarios is equal to the number of origins. In both cases, the smuggler is adaptive in that their optimal path depends on where we locate detectors. We note that while we do use equally-weighted probabilities as described here in our analysis, the model that we use can also handle a probabilistic smuggler with unequal weights on origins and destinations and an adversarial smuggler with unequal weights on the origins.

3.2. PARAMETERS

The following parameters are considered in our model:

- $\lambda \in [0,1]$ represents the weight of the evasive smuggler objective function. A higher value of λ indicates a greater emphasis on interdicting the evasive smuggler (that is, minimizing evasion probability for the evasive smuggler). Conversely, a lower value of λ puts emphasis on screening as much traffic volume as possible. Thus, the optimal solution for a value of $\lambda = 0$ is the list of ports of entry in descending order of volume. This parameter affects our strategy in installing detectors at POEs.
- $q_k \in [0,1]$ represents the evasion probability through a POE k, given that a detector is in place. That is, q_k denotes the inefficiency of the detectors at k. We begin by assuming that the detectors are perfectly reliable (that they will sound an alarm 100% of the time if a smuggler tries to go through) but relax this assumption in our sensitivity analysis to see whether this affects solutions. These parameters affect the structure and evasion probabilities of the network.
- Port of entry evasion probabilities for different modes: these parameters represent the intrinsic probability that a smuggler would not get caught at a POE in the absence of a detector. These values can vary depending on the type of POE. These parameters affect the structure and evasion probabilities of the network.

- Fixed rates on network arcs (α): These parameters impose a decrease in the evasion probability on arcs in the network relative to their length. We have a separate fixed rate parameter for each of the three network modes (α_{rail} for rail, α_{road} for road and α_{sea} for sea). These parameters affect the structure and evasion probabilities of the network.

As noted above, fixed rate and border crossing evasion probability parameters affect the indigenous evasion probabilities that a smuggler faces. We use them, along with the q_k parameters, to compute the evasion probabilities for the evasive and volume smugglers, $h_E(x, \omega)$ and $h_V(x, \omega)$.

In the case of the evasive smuggler this is done as follows: For each smuggler ω and point of entry k we compute the value of the maximum-reliability path from smuggler ω's origin to the entrance to k, say $\gamma_{k,1}^{\omega}$, and the value of the maximum reliability path from the exit from k to the smuggler's destination, say, $\gamma_{k,2}^{\omega}$. These maximum reliability paths are computed as the products of the evasion probabilities of each of the arcs in the path. The evasion probability of an arc going from node i to node j is

$$p_{ij} = e^{-\alpha d_{ij}}$$

where d_{ij} is the length of the arc and α is the fixed rate that is determined by the mode of transportation on that arc; i.e., $\alpha = \alpha_{rail}$ or $\alpha = \alpha_{road}$ or $\alpha = \alpha_{sea}$. These p_{ij} values are used in computing the $\gamma_{k,1}^{\omega}$ and $\gamma_{k,2}^{\omega}$ terms by solving a maximum-reliability path problem, which, in turn, can be reduced through a logarithmic transformation to a shortest path problem. Note that the evasion probability of a path between any two nodes is computed as the product of the evasion probabilities on all the arcs traveled between the two nodes since we assume that these evasion events are independent. Thus we obtain the value of the maximum reliability paths from origin to point of entry $\gamma_{k,1}^{\omega}$ and from point of entry to destination $\gamma_{k,2}^{\omega}$. If we call the product of these two probabilities $\gamma_k^{\omega} = \gamma_{k,1}^{\omega}\gamma_{k,2}^{\omega}$, then the evasion probability for an evasive smuggler ω is given by

$$h_E(x,\omega) = \max_{k\in K}\{\gamma_k^{\omega} p_k(1-x_k), \gamma_k^{\omega} p_k q_k x_k\}$$

where p_k is the evasion probability through POE k if no detector is installed there, determined by its mode.

In the case of the volume smuggler, what we are concerned the probability that a smuggler passes through a POE that does not have a detector installed, given that the choice of where to enter the country depends on the proportion of the total volume coming through each POE. We assume that the volume smuggler can get from their origin to the border with an evasion probability of 1, and from the border to their destination with an evasion probability of 1, since the volume smuggler objective is simply a measure of how much traffic gets screened. Therefore, the evasion probability for volume smuggler ω is given by

$$h_V(x,\omega) = \sum_{k\in K} \pi_k * \max\{p_k(1-x_k), p_k q_k x_k\}$$

where π_k is the proportion of all volume that goes through POE k.

In our analysis, we vary the q_k, fixed rate and border crossing evasion probability parameters in an attempt to accurately model existing conditions, achieve realistic smuggler movement and test the robustness of the model and our assumptions. We also vary λ to observe the effects of the two competing objective functions on solutions.

3.3. SOLVER

Solutions to the model are computed by custom-made solver algorithms implemented by Michael V. Nehme (see Nehme [9]). The model is solved to optimality for each budget value. Furthermore, a heuristic method is used to find nested solutions. We discuss in more detail the notion of nested solutions below.

3.3.1. Optimal solver

The model is solved as a stochastic network interdiction problem defined on top of a maximum-reliability path problem, where installing a detector at a POE is represented by changing the evasion probability on the arc through that POE. The model can be reformulated and solved as a stochastic mixed integer program. Pan and Morton [12], Nehme and Morton [11] and Dimitrov et al. [4] discuss the solver algorithm and computational enhancements in more detail. For every budget value b, the optimal solver returns the set of detector locations which minimize the smuggler's evasion probability.

3.3.2. Nested (heuristic) solver

The optimal solution may not be practically applicable, because the set of secured POEs for different budget values can vary dramatically. For example, suppose there are 20 land POEs a smuggler could choose from when coming into the U.S. from Mexico, and 30 when coming from Canada. In this scenario, the optimal solution for a budget of 20 may be to secure the Mexican Border in its entirety, while a budget of 30 may have those detectors be of better use when placed on the Canadian border, leaving the Mexican border open. Obviously, this is not practically feasible since it does not make sense to move installed detectors. A more realistic policy is to build up and strengthen infrastructure over time. The heuristic solver works towards this goal. This solver builds a priority list of the order in which to improve detection capability at POEs. That is, the heuristic solver gives us nested solutions: the POEs that are secured for a budget value of b are also required to be used for all budget values greater than b. The particulars of obtaining such nested solutions are discussed in greater detail in Nehme and Morton [10].

3.4. SOLUTION FORM

Both the nested and optimal solvers determine the best placement of detectors along the border for each possible budget value *b*. The solvers return as output the locations of the detectors (i.e., the ports of entry *k* for which $x_k = 1$), the evasion probability and coverage with these detectors in place, as well as the weighted objective function value for the particular arrangement, dependent on λ. In addition to this, we generate plots demonstrating the best locations for detectors and highlighting smuggler's preferred routes for different budget values.

It is important to note that when we report overall system evasion probabilities, we rescale these so that the evasion probability with no detectors in place equals 1. This means that we cannot directly compare the evasion probabilities or composite objective function values for scenarios wherein parameter values affect the indigenous evasion probability of the complete network, unless we reverse this scaling.

4. Data

Obtaining useful and significant results from the above model requires substantial data. Of course, we need to know K (our set of potential detector locations), as well as potential smuggler origins and destinations. We also need to know the transportation network, with all of its connections and possible routes, to determine how a smuggler would travel between an origin and a destination.

4.1. The network

The transportation networks used to model this problem come from the PATRIOT database of Los Alamos National Laboratory. The PATRIOT database defines a global transportation network across different modes. One of its main features lies in the given arc reliabilities, which lies in the given arc evasion probabilities. For our problem we crop the network to only include desired modes of transportation (rail, road and sea) and applicable geographic territories. Further, we institute a penalty on evasion probability for switching modes, representing the risk of the smuggler being caught by authorities at a railroad station or sea port when transferring to a different transportation network.

4.2. Origins and destinations

Recognizing that the specific selection of origins and destinations may affect the solution, careful consideration went into choosing which cities to use in our analysis. These were selected to capture significant geographical diversity while also describing credible threats.

4.2.1. Origins

We consider 12 origins in total. We have three origins in each of Mexico and Canada, spread across each country, to model threats from different potential locations. These are listed below.

- San Luis Potosi, Mexico
- Chihuahua, Mexico
- Nuevo Casas Grandes, Mexico
- Toronto, Canada
- Winnipeg, Canada
- Calgary, Canada

While it is unlikely that nuclear materials of the type we are considering would in fact originate in Mexico or Canada, these origins were selected to account for scenarios in which a smuggler first successfully travels to North America and then attempts to enter the United States. A smuggler starting at any of these origins has at their disposal road and rail networks to try to get into the United States. The implicit assumption here is that if a smuggler decided to go to either Canada or Mexico en route to their destination, then they would not leave these countries except to get into the United States.

In addition to the origins listed above, we consider six origins spread across Europe, Africa and Asia. These selected origins represent the aggregated threat from outside of North America. They are:

- Jakarta, Indonesia
- Cirebon, Indonesia
- Islamabad, Pakistan
- Rotterdam, The Netherlands
- Istanbul, Turkey
- Cape Town, South Africa

To get to the United States from any of these, a smuggler would have to travel by sea in our model. A smuggler originating in Asia has the ability to travel across the Pacific Ocean to any sea POE on the west coast of the United States, while a smuggler coming from Africa or Europe can cross the Atlantic to any U.S. sea POE on the east coast or in the Gulf of Mexico.

By having an equal number of origins targeting each U.S. border, we try to eliminate the possibility that our solutions are distorted by an imbalance of threats coming from a certain direction.

4.2.2. Destinations

The destinations we consider are large cities in the United States, assuming that a smuggler's target would be somewhere where they could cause significant damage. Destinations are spread across the country, although we do have a greater concentration of destinations in the east, representative of the population distribution in the United States. Below is a list of the 10 destinations.

- New York City, NY
- Philadelphia, PA
- Washington, D.C.
- Atlanta, GA
- Chicago, IL
- St. Louis, MO
- Houston, TX
- Denver, CO
- Los Angeles, CA
- Seattle, WA

4.3. Ports of Entry

In choosing potential detector locations, we consider only commercial POEs. For volume measures we consider foreign container cargo and shipments processed by these POEs over the course of one calendar year. The total volume processed through the POEs is over 26 million containers.

4.3.1. Rail

Data on rail POEs were obtained from the Bureau of Transportation Statistics' database on North American Border Crossing/Entry Data 2009 [14]. This was cross-referenced with records on the U.S. Customs and Border Protection website [15]. We consider POEs into the contiguous 48 states. As noted above, we are only interested in commercial POEs. In the context of rail, these are POEs with at least one loaded or empty rail container going through over the course of the year in question. Our volume measure, used to model the volume smuggler, is *Loaded Rail Containers*.

The end result is a list of 29 POEs, seven on the Mexican border, 22 on the Canadian border. Combined, these rail POEs handle 5% of total foreign container traffic into the United States.

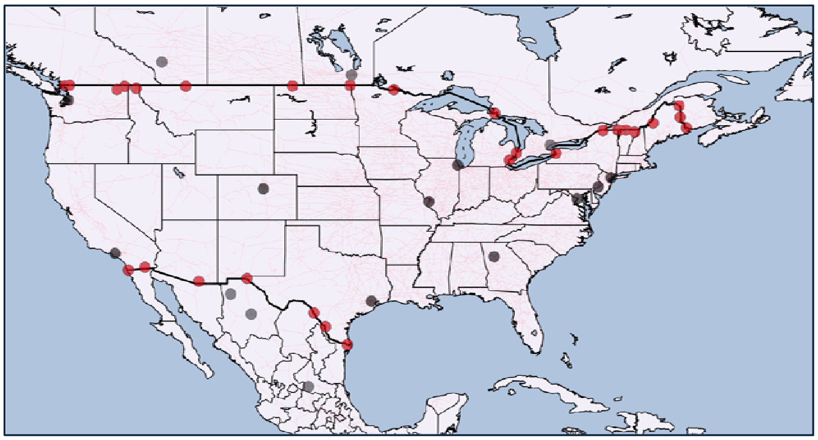

Illustration 4.1: Rail ports of entry

4.3.2. Road

As for rail POEs, data on road POEs were obtained from the Bureau of Transportation Statistics' database on North American Border Crossing/Entry Data 2009 [14] and cross-referenced with records on the U.S. Customs and Border Protection website [15]. Again, we consider only commercial POEs into the contiguous 48 states. In the context of road, a commercial POE is one with at least one loaded/empty truck container going through during the calendar year. The volume measure used for road POEs is *Loaded Truck Containers*.

Bureau of Transportation Statistics data for road POEs are aggregated in some cases, and we may see one port authority responsible for the administration of multiple POEs. In these instances, we treat the data as follows: Where data for multiple small POEs were aggregated, we distribute the reported volume evenly among the POEs; where data for multiple POEs in single a metropolitan area or very close proximity to one another were aggregated, such as is the case in Laredo, TX and Detroit, MI, we treat all these border POEs as a single POE with the notion that upgrades to their detection capability would occur in unison.

The end result is a list of 112 road POEs, 21 on the Mexican border and 91 on the Canadian border. Combined, these road POEs account for 25% of all foreign container traffic coming into the United States.

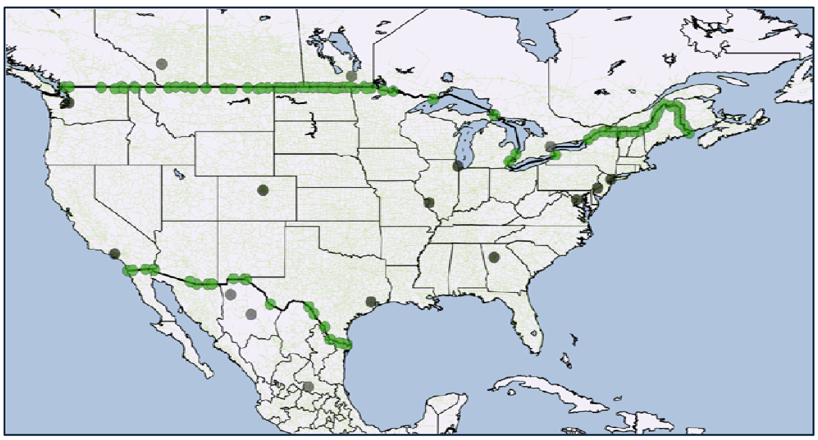

Illustration 4.2: Road ports of entry

4.3.3. Sea

We only consider container ports as sea POEs into the United States. This allows us to use a common unit for comparing volumes through POEs on different transportation networks. The data on sea POEs were obtained from Zepol's 2009 U.S. Containerized Import Ports Report [16], and again cross-referenced with the U.S. Customs and Border Protection website [15]. As with rail and road before, we consider POEs into the contiguous 48 states. Our volume measure in this case is twenty-foot equivalent units (TEUs), representing a 20ft container.

The end result is a list of 46 sea POEs, 11 on the west coast and 35 on the east coast and Gulf of Mexico. Combined, these sea POEs process 70% of all foreign container traffic coming into the United States.

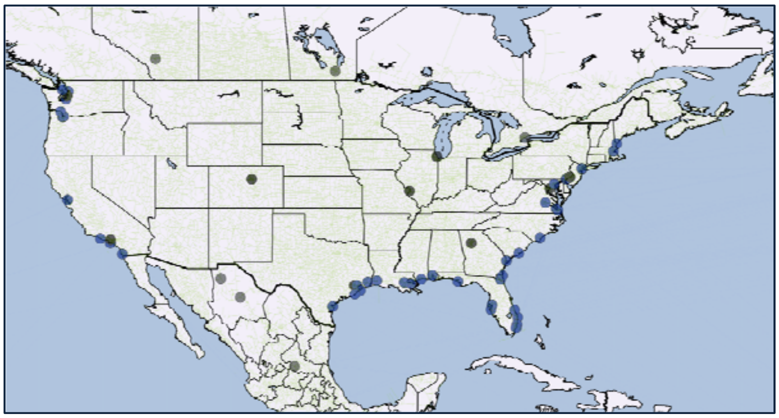

Illustration 4.3: Sea ports of entry

We have a total of 187 ports of entry into the U.S. across all three transportation networks. All 187 of these are presented in the Appendix to this article.

5. Results

We consider the probabilistic and adversarial models separately. For each, we present a base case determined by the value of parameter λ, the characteristics of the optimal and nested solutions for this base case, as well as comparisons to results for different values of λ.

5.1. PROBABILISTIC MODEL BASE CASE

The base case represents the situation where we are foremost concerned with an intelligent, informed and adaptive adversary. Still, we put some weight on the volume base smuggler to represent a preference for improving detection capability at high volume ports when significant improvements for an evasive smuggler are not possible. The chosen value of λ offers a good compromise between the two competing objective functions. Specifically, we observe very little loss in evasion probability performance as compared to the purely evasive smuggler scenario, while simultaneously getting large gains in coverage (see Table 5.1).

5.1.1. Parameter values

The parameters for the base case are as follows:

- $\lambda = 0.8$, meaning that the weight on the evasive smuggler objective is four times that for the volume smuggler.
- $q_k = 0$, meaning perfectly reliable detectors at all ports of entry.
- Fixed rates on network arcs: $\alpha_{rail} = 0.00033334$; $\alpha_{road} = 0.00008$; $\alpha_{sea} = 0$. The choice of these α parameters decreases evasion probabilities for road travel by a factor of 0.923 for 1000km traveled by road, and 0.717 for the same distance traveled by rail.

- Port of entry evasion probabilities for different modes: 0.85 for rail, 0.75 for road, 0.65 for sea. These parameter values were chosen to describe what we deem to be differences in a smuggler's evasion probability when going through a POE on a particular mode, in the absence of a detector.

For the probabilistic model, in the absence of detectors at any of the POEs into the United States this base case yields the smuggler paths illustrated in Illustration 5.1.

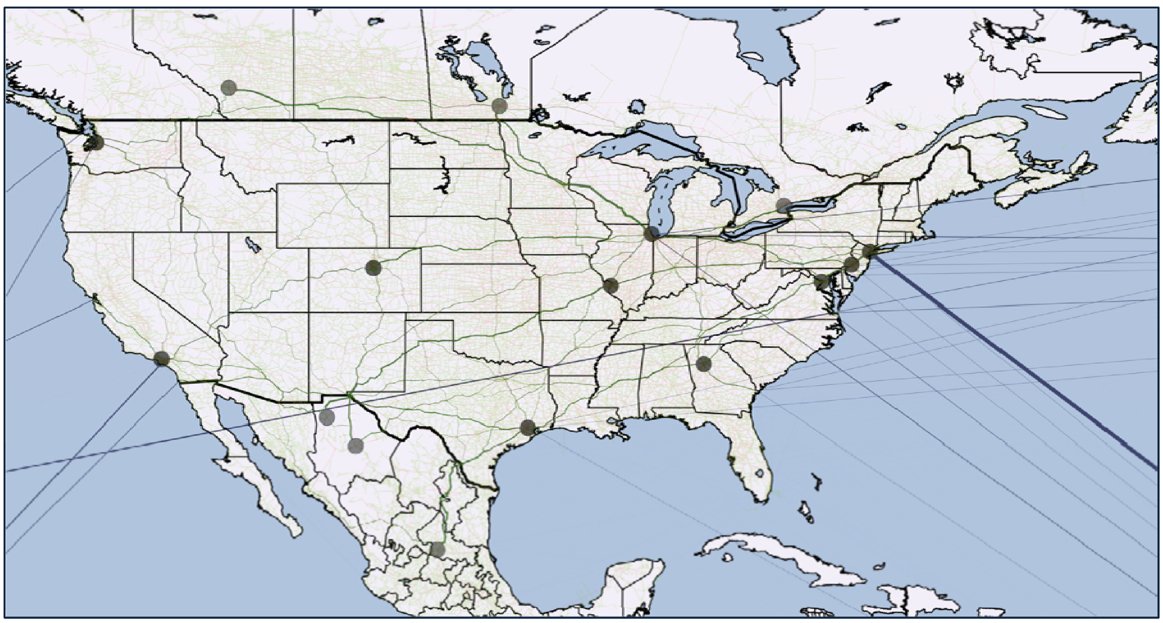

Illustration 5.1: No detectors installed (probabilistic model, $b = 0$).

5.1.2. Optimal solution

We now walk through the optimal solution as we parametrically increase the budget b for the base case described above. The first priority of the optimal solution is to secure high volume POEs on all borders. When $b = 18$, we have secured the 18 highest volume POEs (13 sea ports and five road POEs), which together account for 77.1% of all container traffic. Once this is done, we continue installing detectors at sea ports on the east coast. At b = 23, some detectors are reallocated from the east coast to the west coast, thereby completely securing that border. Going on, we resume securing the east coast.

In the optimal solution for b = 33, at which point we have enough budget to install detectors at all POEs on the Mexican border, we shift resources there. As the budget value b grows larger, we keep the detectors on the Mexican border and resume securing the east coast. We continue to do so until the budget is sufficient to secure all sea ports, thus neutralizing all threats from origins outside of North America. This occurs at b = 46. At this budget value, all detectors are moved to sea ports and the Mexican border is once again left unprotected (see Illustration 5.2 and Illustration 5.3).

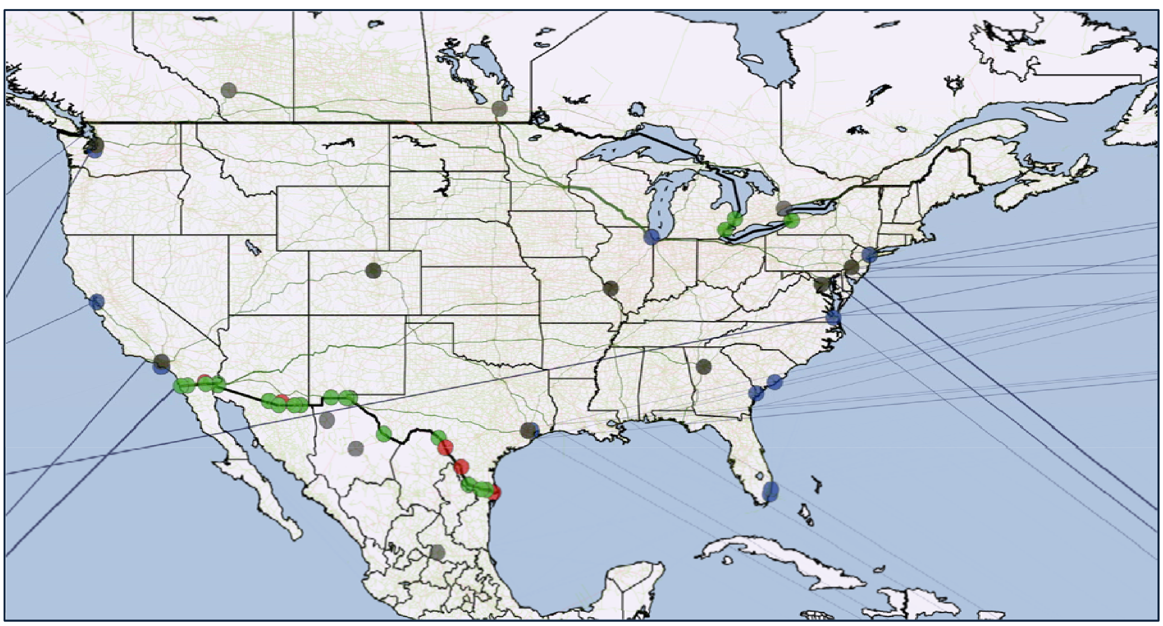

Illustration 5.2: After Mexican border has been secured, continue installing detectors at sea ports (optimal solution for probabilistic model, b = 45).

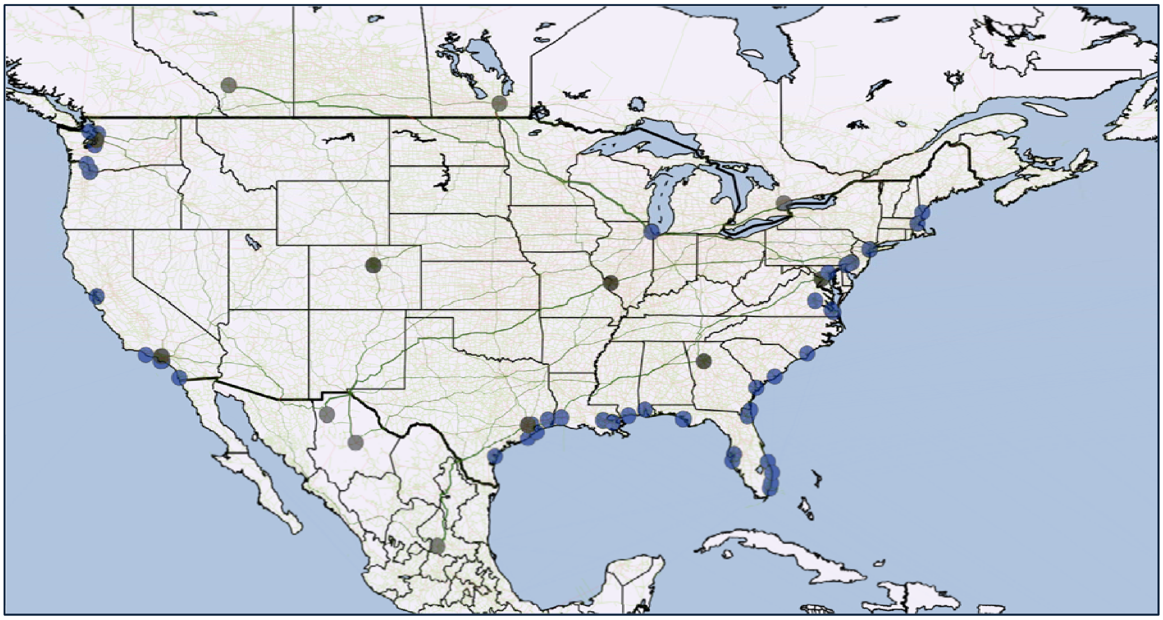

Illustration 5.3: Solution moves all detectors to secure sea ports, once again opening up Mexican border, as soon as budget is sufficient (optimal solution for probabilistic model, $b = 46$).

Once all sea ports are secure, we continue by installing detectors at high volume POEs on the Mexican and Canadian borders. Next, detectors are installed along the Mexican border. This gradually forces smuggler traffic coming through Mexico to take roundabout routes to their destinations, which decreases their evasion probability. When $b = 74$, we have enough resources to secure all 46 sea ports and all 28 POEs on the Mexican border. All detectors on the Canadian border are moved down to the Mexican border, completely closing out smugglers from those origins.

From here on, only the Canadian border is left to secure. We begin doing so by securing high volume POEs once more. Resources intermittently shift east and west of the Great Lakes so as to maximally affect and divert preferred smuggler paths, depending on the number of detectors available. At $b = 134$, all detectors are moved so as to secure the entire Canadian border west of the Great Lakes. This forces a smuggler originating in the middle to western part of Canada to go all the way around the Great Lakes to cross the border, and then back west again so as to reach destinations in the west of the United States. In the process, smugglers travel farther by land, increasing their risk of getting caught by indigenous law enforcement.

As the budget grows larger still, we continue east of the Great Lakes, installing detectors and pushing these paths to destinations in the west farther until a final reallocation occurs at b = 183. At this budget value, detectors from the western-most points on the Canadian border are reallocated so as to completely secure every POE east of the Great Lakes. This results in a greater decrease in the smuggler's evasion probability since the trip required to circumvent secured detectors is longer. Securing all POEs east of the Great Lakes also has a greater effect on the objective function value due to the greater number of threat scenarios affected. This is due to the concentration of destinations in the east.

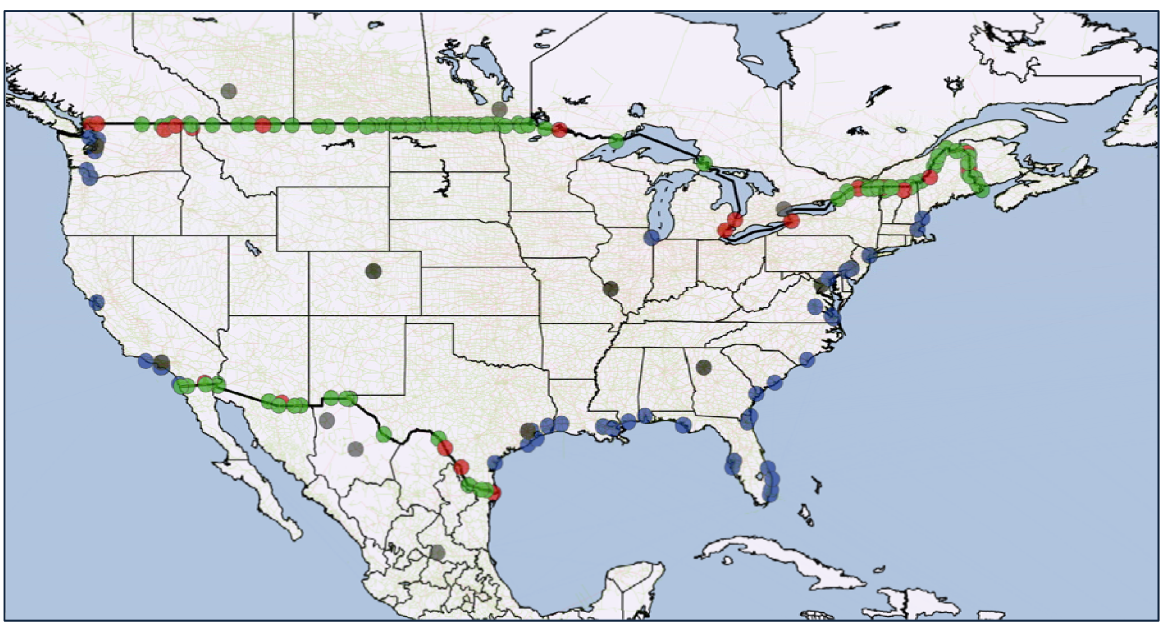

Illustration 5.4: All borders secured (solution for probabilistic model, b = 187).

Finally, all borders are secured at b = 187 (see Illustration 5.4). We note that throughout, a smuggler prefers to travel by road rather than rail, unless their route brings them close to a rail POE, in which case they come into the United States by rail and immediately revert back to traveling by road.

5.1.3. Nested solution

The nested solution starts by securing POEs with the highest traffic. The seven POEs that process the highest volume of incoming containers top the priority list and are the first to have detectors installed. All of these are sea ports: three on the west coast (Los Angeles, CA, Long Beach, CA and Seattle, WA), one in the Gulf of Mexico (Houston, TX), and three on the east coast (New York, NY, Newark, NJ and Savannah, GA). Together, these account for 49.3% of all container traffic coming into the United States. We continue installing detectors at sea ports along the east coast, starting in the southeast with the high volume ports of Norfolk, VA, Charleston, SC, Miami, FL and Port Everglades, FL. Next we secure all remaining sea ports in New England, as well as the one in Chicago, IL. By doing so, we force any smuggler coming from across the Atlantic who targets cities on the east coast to travel farther within the United States, from their entry points in the southeast, to their destinations in the northeast. We continue installing detectors further down the east coast then into the Gulf of Mexico, forcing the smuggler on increasingly longer routes to these destinations. With each additional sea port secured, we see the smuggler's preferred routes become longer. Once detectors are installed at all of the sea ports on the Eastern Seaboard and the Gulf of Mexico, the threat from across the Atlantic (represented by the origins in The Netherlands, Turkey and South Africa) is neutralized. The solution then dictates that we proceed to install detectors at all of the remaining unsecured sea ports on the west coast, starting in California and working up the coast. Again, this makes the smuggler's travel within the U.S. (where indigenous law enforcement presents a risk) incrementally longer, thereby decreasing their evasion probability. Finally, at a budget value of b = 46, all sea ports into the United States have detectors installed and there is no threat coming in by sea (that is, from outside of North America).

The high prioritization of sea ports on the east coast is most likely due to the concentration of potential destinations there. Since the probability of a smuggler getting caught is much greater when traveling by land than by sea, a smuggler would prefer to come in to the country as close to their destinations as possible. By securing the sea ports nearest to the biggest cluster of destinations, we cause the most inconvenience to the smuggler, as evidenced by the drop in evasion probability (see Figure 5.1). By securing all sea ports first, we neutralize half of the threat scenarios (represented by non-North American origins) at a relatively low cost of b = 46. Furthermore, since sea ports process the majority of foreign cargo coming into the country (just over 70%), by securing them first we also do a good job of thwarting the volume smuggler.

Once detectors have been installed at all sea ports, the solution dictates that we focus our attention on the Mexican border. The first five POEs to have detectors installed are the five highest volume POEs on the Mexican border: the road POEs at Laredo, TX, Otay Mesa, CA, El Paso, TX, Hidalgo, TX and Nogales, AZ. Together, these POEs account for 74.8% of all container traffic coming in through the Mexican border. By securing these POEs first, we seek to maximally impact the volume smuggler. Once these POEs have been secured, we proceed to install detectors along the rest of the border, first heading from Laredo, TX towards the west coast, thus forcing all smuggler traffic from Chihuahua and Nuevo Casas Grandes to travel farther to get into the U.S. Once this is done, we secure the remainder of the Mexican POEs, all of which are in Texas. For a budget value of b = 74, all of these POEs have been secured and the threat from the south has been neutralized (see Illustration 5.5).

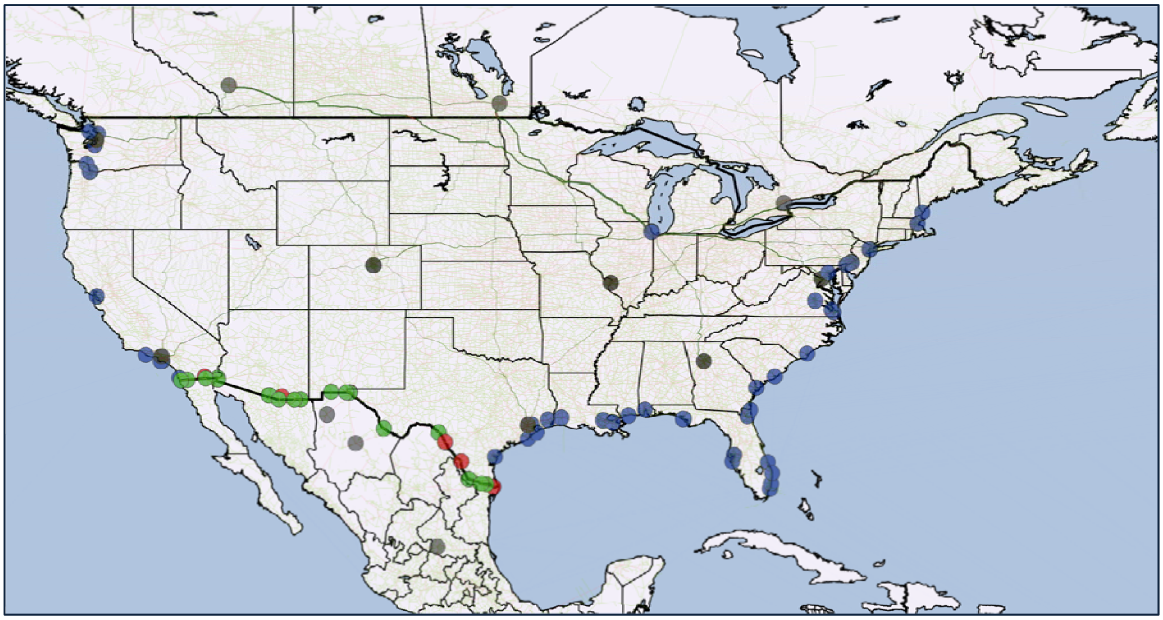

Illustration 5.5: Mexican border and sea ports secured
(nested solution for probabilistic model, b = 74).

After all sea ports have detectors installed, securing either the Mexican or Canadian border would neutralize half of the remaining threat. Since it takes less resources to secure the border with Mexico, these POEs are a higher priority. Simply put, we obtain more significant results by focusing on Mexico than if we were to start installing detectors along the border with Canada. Since the benefit of completely securing an enitre border is greater than diverting a smuggler from their preferred routes, we see that no resources are allocated to the Canadian border until the Mexican border is secure.

Once the Mexican border is secure, all that remains is installing detectors along the United States border with Canada. As with Mexcio before, we start by securing the highest volume POEs. In this case, the following 11 POEs are secured: rail and road POEs in Detroit, MI and Port Huron, MI, road POEs in Buffalo, NY, Champlain, NY, Blaine, WA, Alexandria Bay, NY and Pembina, ND, and the rail POE in International Falls, MN. Together, these POEs account for 73% of all container traffic coming into the United States from Canada by land. Next, focus is shifted to securing the 50 remaining POEs east of the Great Lakes, with the solution sporadically jumping west to secure a high volume POE. The majority of these 50 POEs are in Maine, and are very close to each other. Because of this, there is very little benefit to securing some of these POEs and not all, as an evasive sumggler would be able to enter the country through any adjacent unsecured POE with little impact on their evasion probability. It may seem counterintuitive that so much emphasis is placed on securing these POEs before securing the rest of the border, but their importance lies in their proximity to the destinations in the east of the United States.

After detectors have been installed at the New England POEs, we proceed west from the Great Lakes, systematically securing POEs heading further west. Doing so forces all smuggler traffic to travel farther west through Canada to get into the United States, and then farther east through the U.S. to the destinations in the east (see Illustration 5.6).

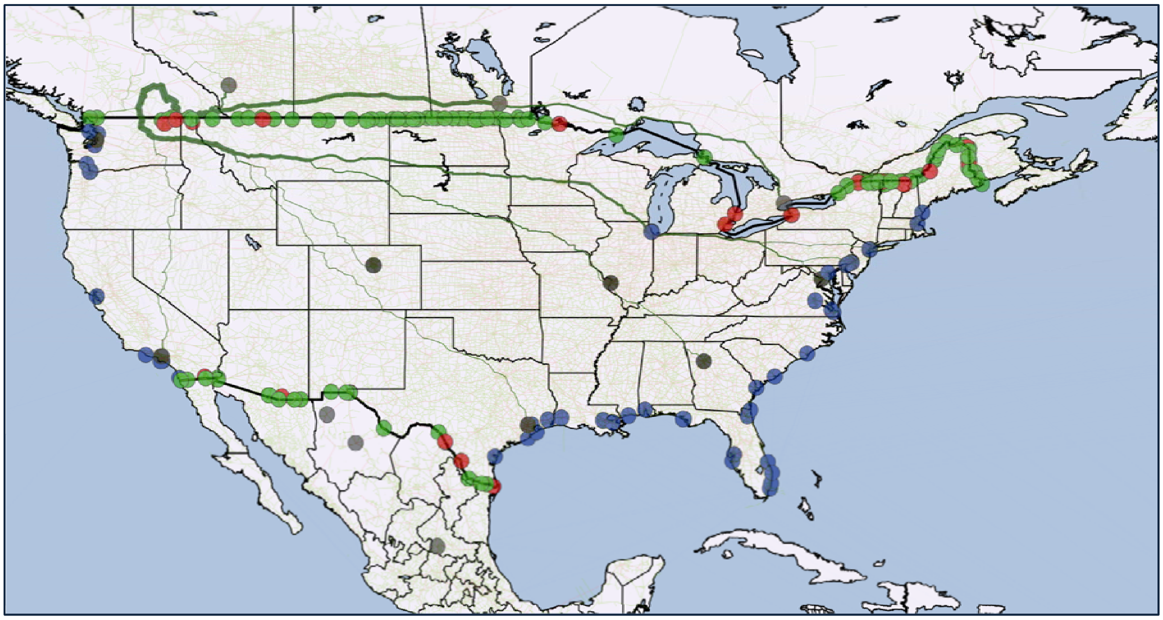

Illustration 5.6: Smuggler routes are forced west by securing ports of entry along the Canadian border (nested solution for probabilistic model, b = 183).

As stated above, we decrease the smuggler's evasion probability by making preferred routes increasingly longer, which poses greater risk of interdiction by indigenous law enforcement. Finally, at a budget value of b = 187, all POEs into the United States have detectors installed and the borders are secure.

5.1.4. Comparing nested and optimal solutions

The nested and optimal solutions are identical at pivotal budget values: the nested solution is the same as the optimal for a budget value b = 46, when all detectors are placed at sea ports completely blocking traffic from outside North America, and for b = 74, at which point the Mexican border is secured in addition to all sea ports (see Figure 5.1). In terms of performance, there is a relatively small difference between the nested and optimal solutions. The optimal solution offers 3.3% better evasion probability and 4.0% better coverage, on average. While there is a strong emphasis on securing the highest volume POEs at first, the nested solution mostly improves the weighted objective function value by systematically securing POEs so as to decrease evasion probability as quickly as possible. The optimal solution, on the other hand, first seeks to achieve a better objective value by increasing coverage, and then reallocates resources when a large decrease in evasion probability can be achieved. The points at which this is possible are where the two solutions are identical.

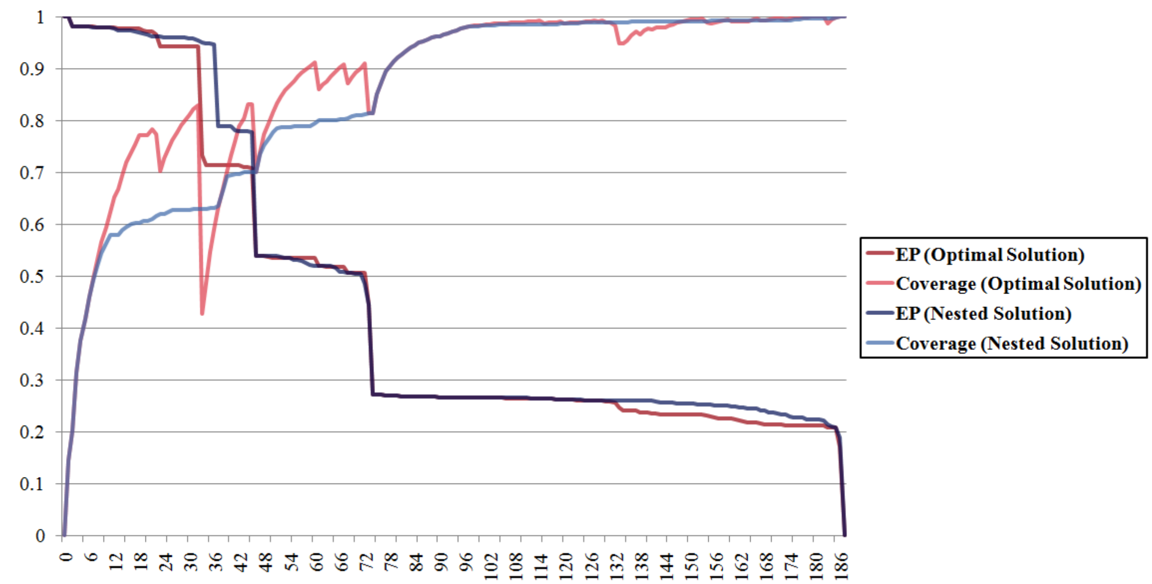

Figure 5.1: Difference in evasion probabilities and coverage between optimal and nested solutions (probabilistic model, $\lambda = 0.8$).

The optimal solution's erratic behavior is clearly visible in Figure 5.1. Note how, at $b = 33$ we see a major drop in evasion probability, coupled with a corresponding drop in coverage. This is the point where detectors are moved from sea ports to the Mexican border. For values of b below 33, resources are better allocated to securing sea ports, due to their high volume. This increase in coverage improves our composite objective function value, which takes into account both our goals in the forms of the evasive and volume smugglers. However, when enough resources exist to secure Mexico and achieve a big drop in evasion probability, most of the detectors are shifted there. Up until this point, the values of the composite objective functions are very close, but for b = 33 the optimal solution's objective value is 15% better than that for the nested, and continues to get better. For b = 36, the optimal solution outperforms the nested solution by 21%. Other than this though, the nested solution objective function value is always within 10% of the optimal and is only 3.9% worse on average.

5.1.5 Changing λ

As discussed in the model formulation (see Section 3.1), we can represent evasive and volume smugglers by two competing objective functions. Changing λ changes the importance of thwarting a volume smuggler versus the importance of thwarting an evasive smuggler. Therefore, by varying λ, we can examine the effects of different policy goals. It is important to find a suitable balance between these competing objectives, and to determine what effect changing the relative weight of each objective has on the priority ranking of POEs. Our base case has an interesting property, namely the grouping in the priority list of POEs in the same region. We see that all POEs on the Mexican border get secured in order, as do all east coast sea ports, and all Canadian POEs. We can think of this as geographic clustering. This is very important, because it demonstrates the existence of an overarching logic to the ranking in the priority list. That is, the exact order in which we secure POEs is not as important as the order in which we secure regions, as evidenced by the large drops in evasion probability at pivotal budget values. If geographic clustering is maintained across different values of λ, this would be indicative of good performance of our solution regardless of the nature of the threat we face.

5.1.5.1 Increasing λ

By increasing λ, we put more influence on interdicting the evasive smuggler. We should see more sharply decreasing evasion probabilities, at the expense of coverage.

In the case of $\lambda = 1$, the priority list changes somewhat, but changes in priority only occur among (and not across) sea ports, Mexican POEs, and Canadian POEs. For example, we see that now the high volume sea ports in Los Angeles, CA and Long Beach, CA are no longer at the very top of the priority list. Instead, this solution dictates that we secure the entire Eastern Seaboard and the Gulf of Mexico before installing detectors anywhere on the west coast, thereby achieving the benefit of neutralizing all threats coming via the Atlantic at a lower budget value. However, despite this difference and other similar ones on the Mexican and Canadian borders, the geographic clustering of the priority list, in terms of first securing sea ports, then the Mexican border, then the Canadian border, stays the same (see Figure 5.2).

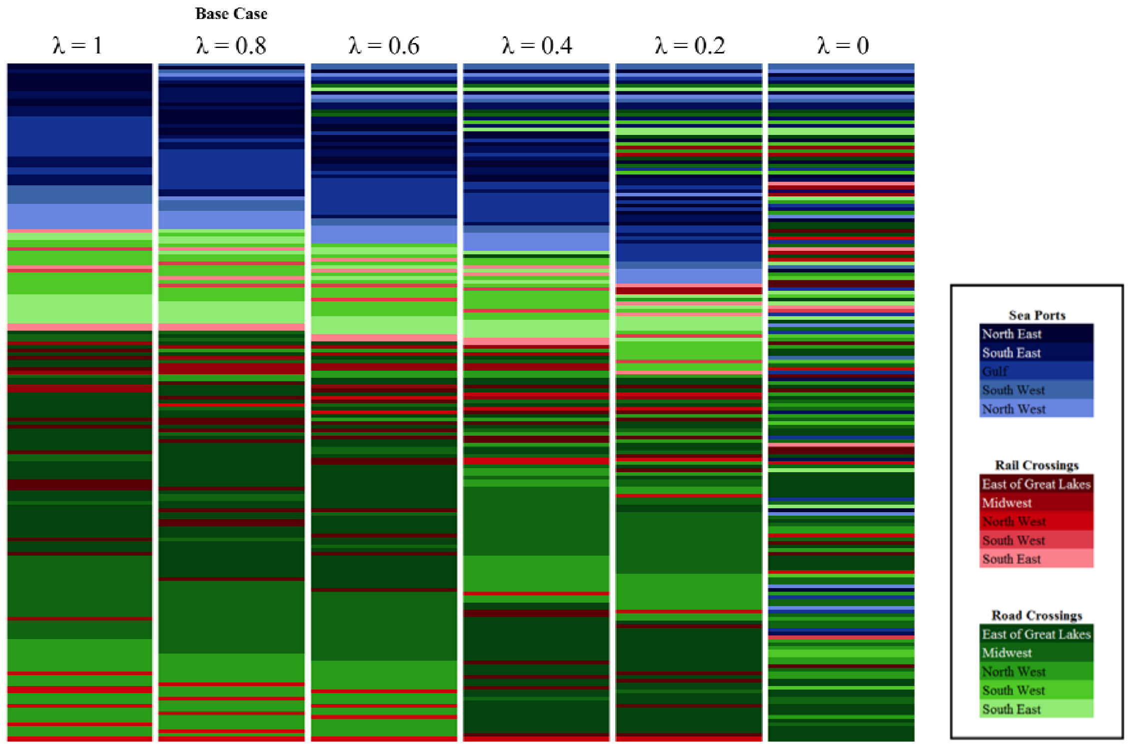

Figure 5.2: Nested solutions for different values of λ (probabilistic model).

5.1.5.2. Decreasing λ

Lower values of λ denote more influence on thwarting the volume smuggler. We can expect coverage to go up in these scenarios, but this would correlate to higher evasion probabilities (see Figure 5.3).

As the value of λ is decreased, the priority list tends more and more towards a volume ranking of POEs. We see that the priority list structure of first securing sea ports, then the Mexican border, then the Canadian border gradually falls apart as λ goes to 0. For example, note that for $\lambda = 0.6$, the solution dictates that we install detectors at the high volume road POEs in Detroit, MI, Laredo, TX, Buffalo, NY and Port Huron, MI before securing all sea ports. This type of change in the priority list becomes more and more prevalent as we decrease λ until, at λ = 0, the priority list is simply a volume ranking of all POEs.

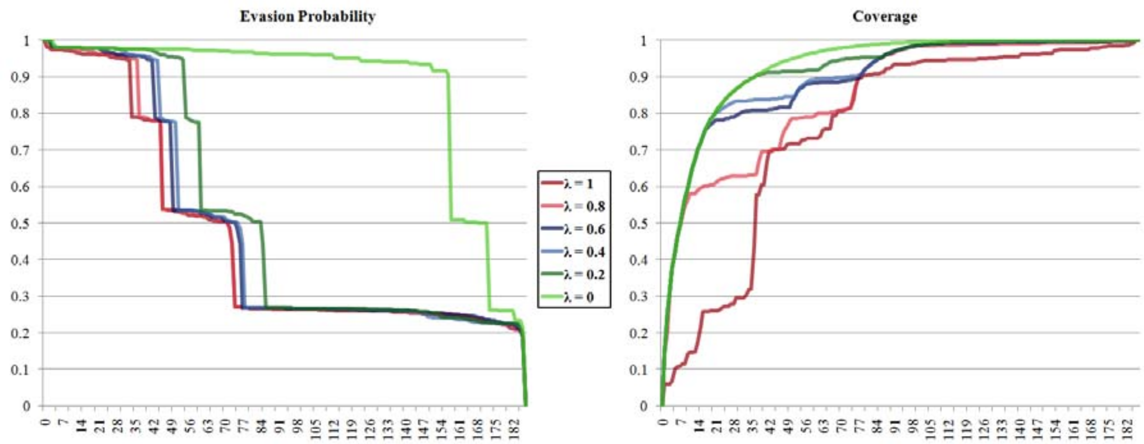

Figure 5.3: Difference in evasion probabilities and coverage between nested solutions for probabilistic model, varying λ.

At our base case of λ = 0.8 there is a good balance in terms of performance based on the two competing objective functions of minimizing evasion probability and maximizing coverage. For this value of λ, neither coverage nor evasion probability is much worse than when the cases when we focus on either of these objectives exclusively (λ = 1 for evasion probability; λ = 0 for coverage).

	λ = 1	**λ = 0.8**	**λ = 0.6**	**λ = 0.4**	**λ = 0.2**	**λ = 0**
Average Difference in Evasion Probability	-1.1%	0%	+3.4%	+4.1%	+12.8%	+141.9%
Average Difference in Coverage	-14.8%	0%	+6.2%	+7.2%	+9.3%	+10.6%

Table 5.1: Probabilistic model nested solution performance, varying λ.

5.2. ADVERSARIAL MODEL BASE CASE

As with the probabilistic model above, the base case represents the situation where we are foremost concerned with an intelligent, informed and adaptive adversary, while still putting some weight on the volume-based smuggler to represent a preference for improving detection capability at high volume ports. Again, the chosen value of λ offers a good compromise between the two competing objective functions and we observe very little loss in evasion probability performance as compared to the purely evasive smuggler scenario, while simultaneously seeing big gains in coverage (see Table 5.2).

5.2.1. Parameter values

The parameter values used in the base case for the adversarial model are the same as those used in the base case for the probabilistic model detailed in Section 5.2. The values for λ, q_k, the fixed rates α_{rail}, α_{road} and α_{sea}, as well as the border crossing detection probabilities for the different modes are identical to the values specified in Section 5.1.1.

For the adversarial model, in the absence of detectors at any of the POEs into the United States this base case yields the smuggler paths illustrated in Illustration 5.7. Note how a smuggler starting at each origin chooses to go to the destination closest to them. For example, a smuggler coming across the Atlantic chooses New York City, NY as their target destination, as the path to this destination has the highest evasion probability.

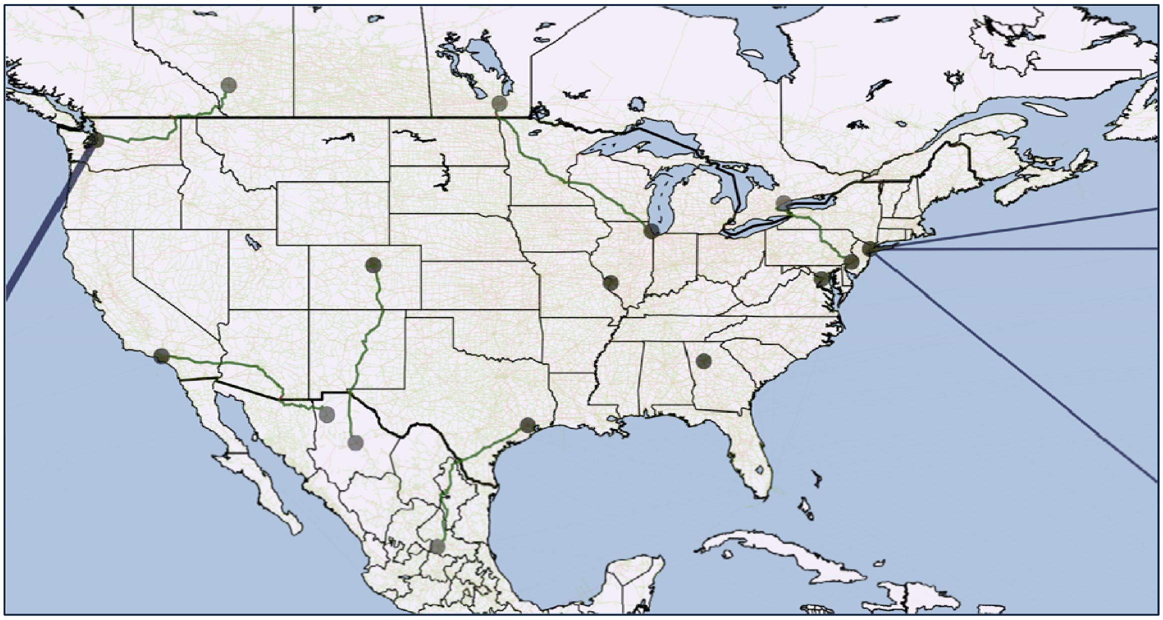

Illustration 5.7: No detectors installed (adversarial model, $b = 0$).

5.2.2. Optimal solution

As in the case of the probabilistic model analyzed in Section 5.1, we walk through the optimal solution as we parametrically increase the budget value b for the base case described above. The optimal solution starts by securing the POEs with the highest volume of traffic. This trend continues as b increases until $b = 25$ and detectors shift to the Texas-Mexico border. A smuggler originating in San Luis Potosi, Mexico then diverts from Houston, TX to Los Angeles, CA.

Next, we proceed by adding detectors at high volume sea ports. When the budget value reaches $b = 33$, most of these detectors are reallocated to secure the Mexican border entirely, neutralizing the threat posed by a smuggler that originates in Mexico (see Illustration 5.8). For subsequent increases of b, we continue adding detectors at the highest volume POEs. When $b = 52$, this secures the east coast of the United States (excluding the Gulf of Mexico), and a smuggler coming from across the Atlantic now prefers to target Houston, TX. As b continues to increase, we allocate detectors to high volume land POEs along the Canadian border. When b = 64, we reallocate detectors to the Gulf of Mexico because enough resources exist to secure all remaining ports there. By moving all detectors to the sea ports on the Gulf of Mexico, we neutralize threats coming from across the Atlantic.

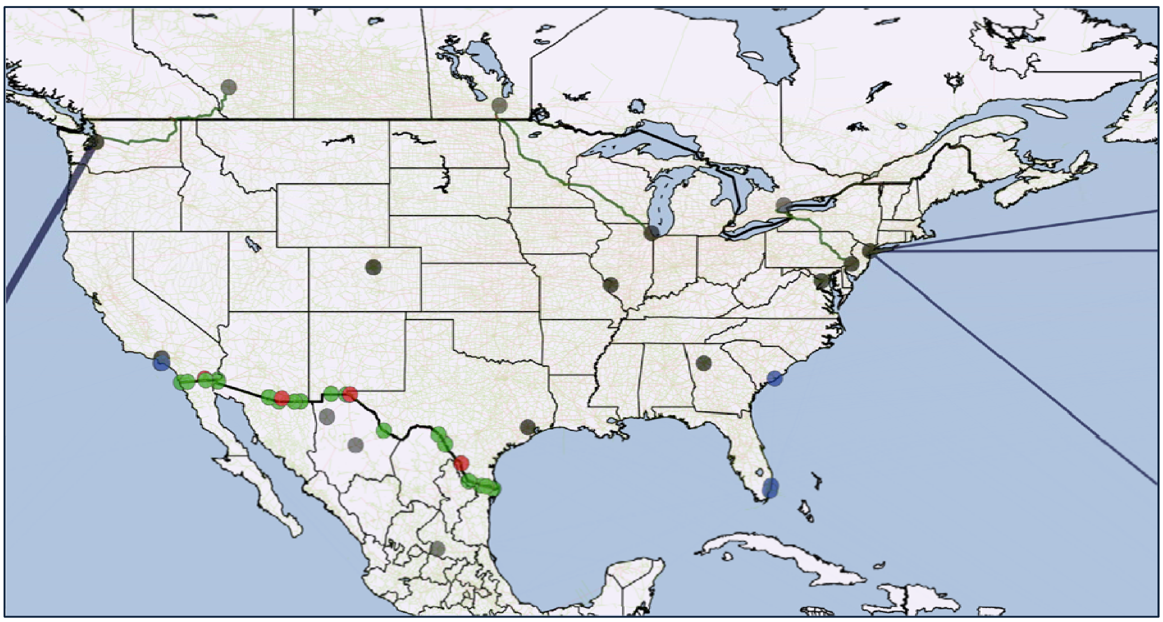

Illustration 5.8: Mexican border secured (optimal solution for adversarial model, b = 33).

At b = 79, all the west coast sea ports are secure. For values of b up to 100, we place additional detectors at high volume POEs on the Canadian border. When b = 101, detectors previously installed east of the Great Lakes are reallocated to the west. This causes a smuggler originating in Calgary, Canada to reroute to Denver, CO instead of Seattle, WA. We continue to add detectors in this direction for values of b up to 125. Again, this lengthens the smuggler's route and decreases their evasion probability.

When b = 126, some detectors are moved from the west coast to the Canadian border. They are used to secure all POEs west of the Great Lakes. This forces a smuggler originating in Calgary, Canada or Winnipeg, Canada to travel around the Great Lakes to enter the United States, lengthening their routes further. The preferred destination becomes New York City, NY. This change does, however, leave the west coast exposed once again.

When b = 136, the west coast is secured, and for subsequent increases in b detectors are installed east of the Great Lakes. This continues until b = 152, at which point detectors from both the east and west coasts are reallocated to completely secure the Canadian border (see Illustration 5.9 and Illustration 5.10).

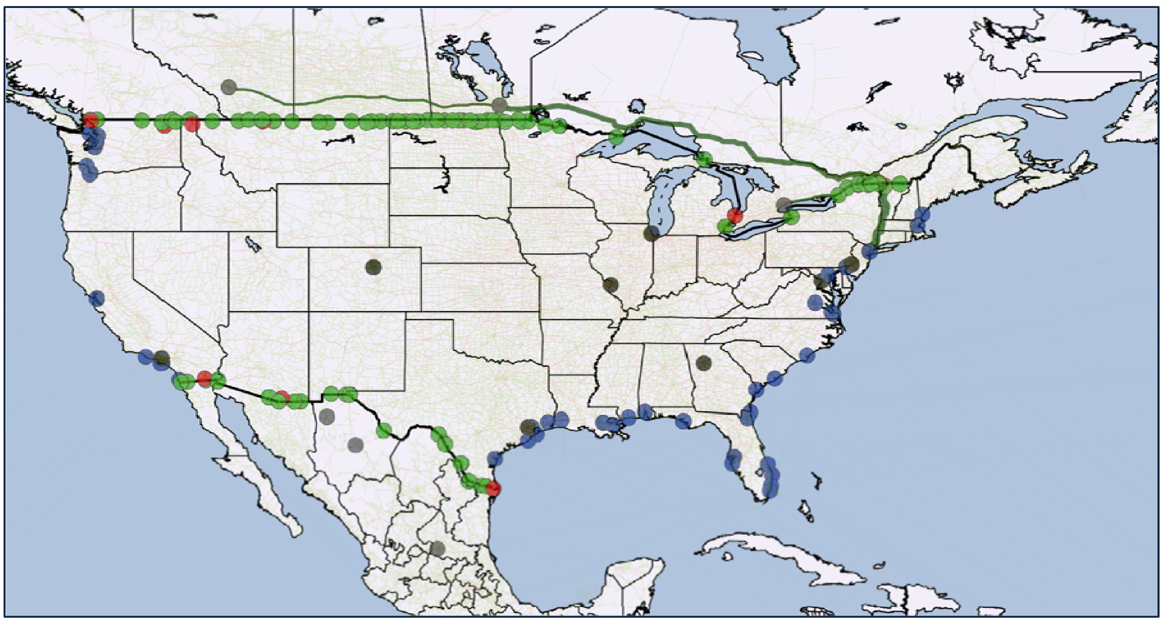

Illustration 5.9: After Mexican border and all sea ports have been secured, continue installing detectors at sea ports (optimal solution for adversarial model, b = 151).

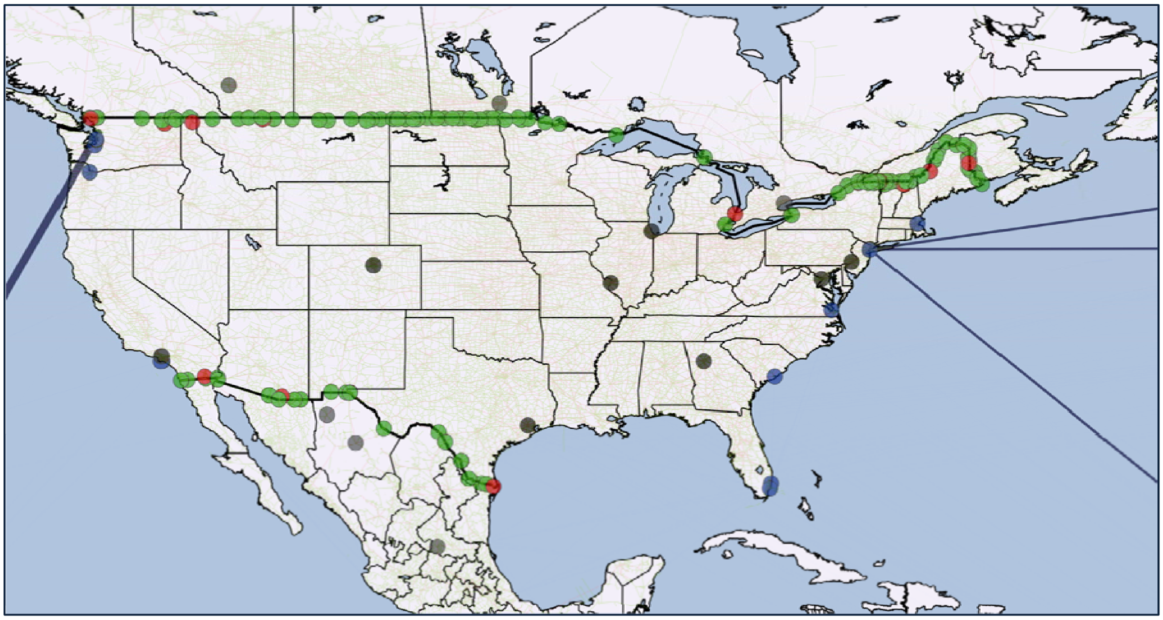

Illustration 5.10: Solution moves detectors from sea ports to ports of entry in Canada as soon as budget is sufficient to secure that border
(optimal solution for adversarial model, b = 152).

From here increases in b gradually build up defenses on the east coast again, securing all POEs there when b = 180, and finally installing detectors at all remaining POEs on the west coast when b = 187. As in the case of the probabilistic scenario, we see that all smugglers prefer to travel by road. Smugglers switch to rail only to decrease route length if the alternative of using a road crossing increases distance and exposure to indigenous law enforcement.

5.2.3. Nested solution

The nested solution for the adversarial smuggler model places the two highest volume POEs (the sea ports at Los Angeles, CA and Long Beach, CA) at the top of the priority list, but then shifts focus to the Mexican border. Starting on the east coast of Texas, detectors are installed along the U.S. border with Mexico as b increases, gradually forcing a smuggler originating there to go farther west, and changing their preferred destinations in the process. The first such change occurs at $b = 16$, where detectors along the Texas border with Mexico make Houston, TX and Denver, CO less desirable destinations for smugglers origination in San Luis Potosi, Mexico and Chihuahua, Mexico respectively. Smugglers originating here now choose instead to go to Los Angeles, CA. With further increases in b, detectors continue to be placed along this border until, at $b = 33$, the entire Mexican border has been secured, just as in the case of the optimal solution (see Illustration 5.8).

As b increases from this point, detectors are placed at the highest volume land POEs on the Canadian border and along the east coast, eventually forcing a smuggler coming across the Atlantic out of New England and instead to Houston, TX when $b = 53$. We continue placing detectors along the east coast and the Gulf of Mexico for additional increases in b. When $b = 70$, all sea ports on the Atlantic Ocean and Gulf of Mexico are secured (see Illustration 5.11).

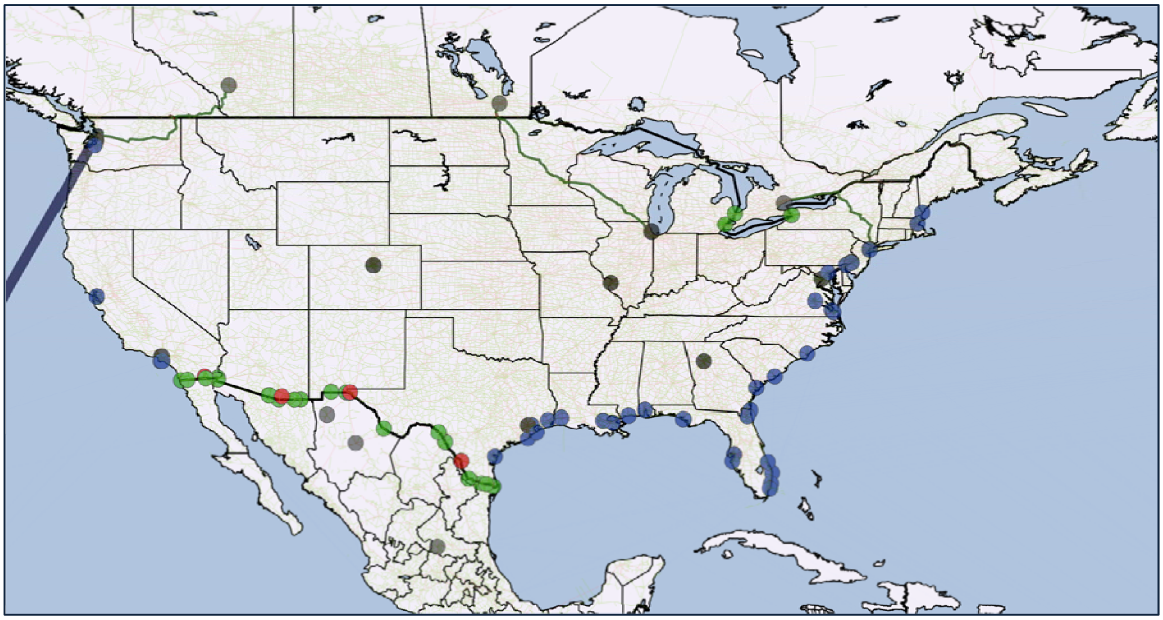

Illustration 5.11: East coast seaports secured (nested solution for adversarial model, $b = 70$).

Once this has been achieved, efforts are focused on the Canadian border. Detectors are installed here, starting at the west coast and moving east for larger values of b, gradually forcing a smuggler originating in Calgary, Canada to travel farther to reach their desired destination of Seattle, WA, until their preference changes to Denver, CO when $b = 100$.

Detectors continue to be installed west of the Great Lakes for additional increases in b, incrementally diverting a smuggler originating in Calgary, Canada and Winnipeg, Canada. When $b = 131$, these smuggler prefers to target Chicago, IL. When $b = 133$ and all POEs west of the Great Lakes have been secured, any smuggler originating in Canada is forced to go along the border to POEs in Vermont, from where they proceed to their destination in New York City, NY. The addition of detectors further east along this border makes this trip ever longer (see Illustration 5.12). Thus, these smugglers' evasion probability gradually decreases, until the entire Canadian border is secure when $b = 181$.

As b increases from this value, the remaining six detectors are installed at sea ports on the west coast, finally securing all borders.

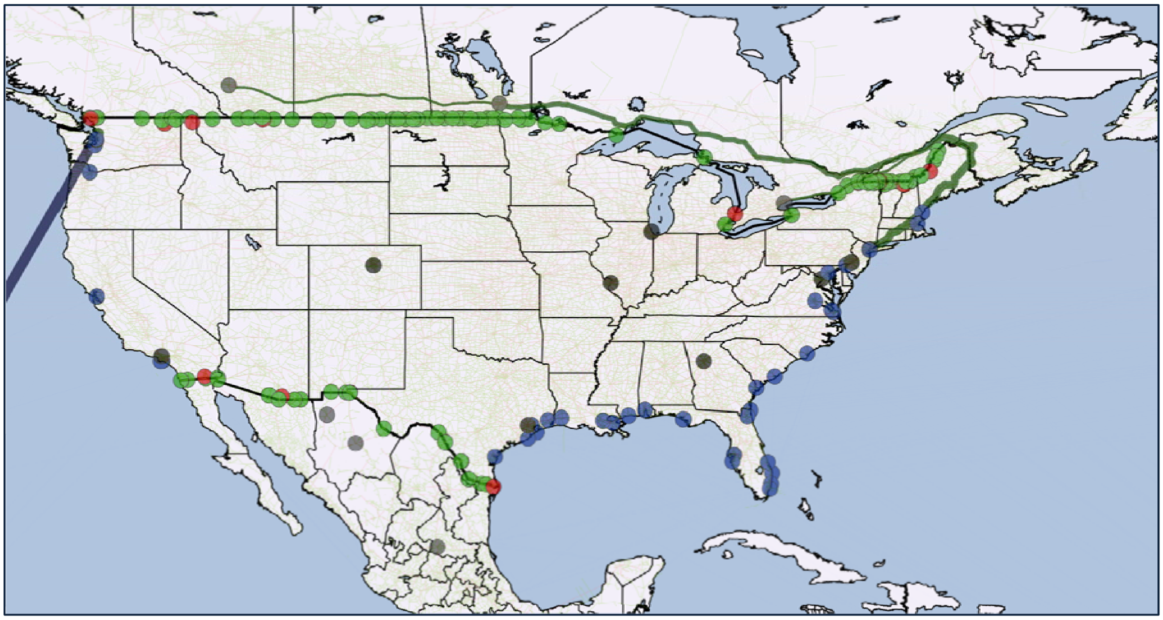

Illustration 5.12: Smugglers originating in Canada pushed east (nested solution for adversarial model, b = 162).

5.2.4. Comparing nested and optimal solutions

In the adversarial smuggler scenario, we see more significant differences between the optimal and nested solutions than we did in the probabilistic model analyzed in Section 5.1. The only (nontrivial) budget values for which the two solutions are identical are b = 33, at which point we secure the Mexican border, and b = 182, when only some west coast sea ports remain unsecured. The results returned by the optimal solver are more variable in this case than in the probabilistic smuggler scenario described in Section 5.1; optimal detector installation sites change more as b increases. As a result, the nested solution performs relatively worse in this scenario than the probabilistic one. There is a larger gap between nested and optimal solutions for almost all budget values, and the nested solution gives 12.3% worse evasion probability and 12.0% worse coverage, on average, than the optimal (see Figure 5.4). This difference is particularly great for budget values greater than 152, the point at which the optimal solution moves detectors away from sea ports to land POEs in New England, so as to secure the Canadian border.

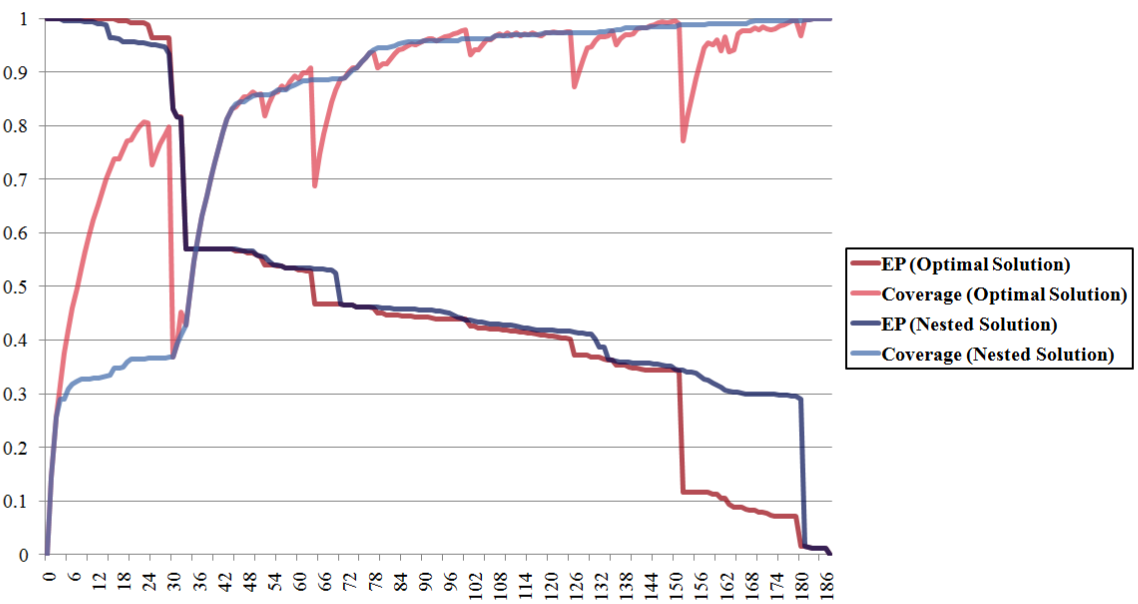

Figure 5.4: Difference in evasion probabilities and coverage between optimal and nested solutions (adversarial model, $\lambda = 0.8$).

Figure 5.4 demonstrates the erratic nature of the optimal solution, with large changes in evasion probability correlating with even larger changes in coverage. The most pronounced of these is at $b = 33$, when many detectors shift from sea ports to the Mexican border. For values of b below 33, resources are better allocated to securing sea ports, due to their high volume. As with the probabilistic model, this increase in coverage improves our composite objective function value. When detectors are reallocated to Mexico we see an even bigger drop in evasion probability than we did in the probabilistic case.

The next big reallocation comes at b = 64, when the east coast and Gulf of Mexico are secured, thereby neutralizing the threat coming from across the Atlantic. Still, this change does not affect the objective function value of the optimal solution very much. In fact, for values of b under 151, the optimal solution objective value is never more than 10% better than that of the nested solution. For b = 152 however, the reallocation of detectors from sea ports to the Canadian border results in a massive drop in evasion probability, at the expense of a smaller change in coverage. At this point, the optimal solution objective function value is 50% better than the nested solution objective value. The benefit to our composite objective function of decreasing evasion probability is significantly greater than that of maintaining increased coverage. This gap in objective function values continues to grow as the optimal solution reaps the rewards of once again securing high volume sea ports, with the optimal solution ultimately being 92% better than the nested solution for b = 181. On average, the optimal solution for the adversarial model performs 12.5% better than the nested, a much greater gap than we see in the probabilistic case.

5.2.5 Changing λ

Similar to the analysis performed in the probabilistic case (see Section 5.1.5), we vary λ to examine the effects of different policy goals on the adversarial smuggler scenario, shifting emphasis between thwarting the volume or evasive smuggler. Again, it is important to find a suitable balance between these competing objectives, and to determine what effect changing the relative weight of each objective has on the priority ranking of POEs. As before, if our sensitivity analysis reveals minimal variation in the priority ranking across different values of λ, this would improve our confidence in the performance of our solution regardless of the nature of the threat we face.

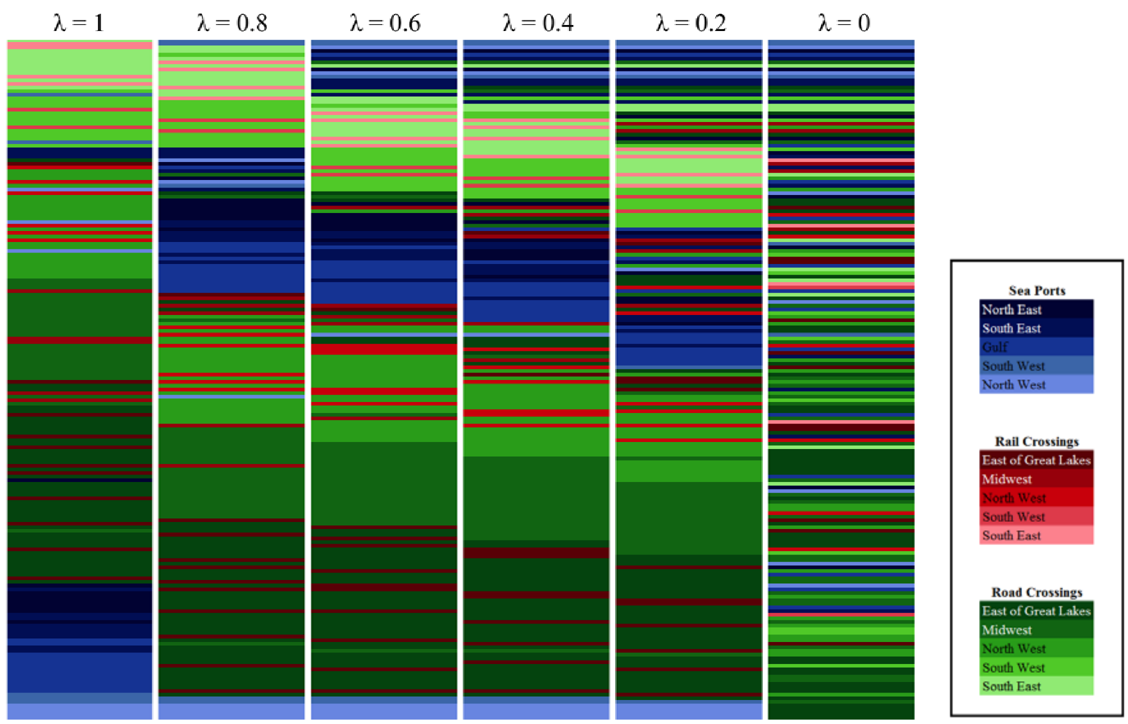

Figure 5.5: Nested solution for different values of λ (adversarial model).

5.2.5.1 Increasing λ

As we discuss in Section 5.1.5.1, higher values of λ give more weight to interdicting the evasive smuggler. When doing so, we should see evasion probabilities decreasing more sharply as our budget b increases, at the expense of coverage.

Unlike in the probabilistic smuggler scenario, drastic changes are observed when varying λ for the adversarial case (see Figure 5.5). For λ = 1, Mexico remains a top priority due to the proximity of potential destinations to origins in Mexico. After that though, only sea ports in the northeast are secured, so as to force a smuggler coming from across the Atlantic to travel further to their preferred destinations. Other sea ports, higher in priority if we put any weight on the coverage objective, fall to the bottom of the priority list. The adversarial model solutions do not have the clear geographic clustering of those for the probabilistic model: the solution sporadically jumps to installing detectors at a sea port in between securing the Mexican and Canadian borders.

5.2.5.2. Decreasing λ

A smaller λ denotes increased weight on thwarting the volume smuggler. As for the probabilistic scenario, we can expect coverage to go up at the expense of evasion probabilities (see Figure 5.6).

The changes in the priority list we see when decreasing λ for the adversarial model are very similar to those discussed in Section 5.1.5.2. Ports of entry on the Mexican border gradually slide down the priority list, replaced by high volume sea ports. Unlike in the case of the probabilistic smuggler model though, sea ports as a group never climb to the top of the priority list. The bulk always remain below Mexican POEs, with some on the southwest staying at the bottom of the priority list for all values of $\lambda > 0$. Ultimately, at $\lambda = 0$, the priority list is once again a volume ranking of all POEs.

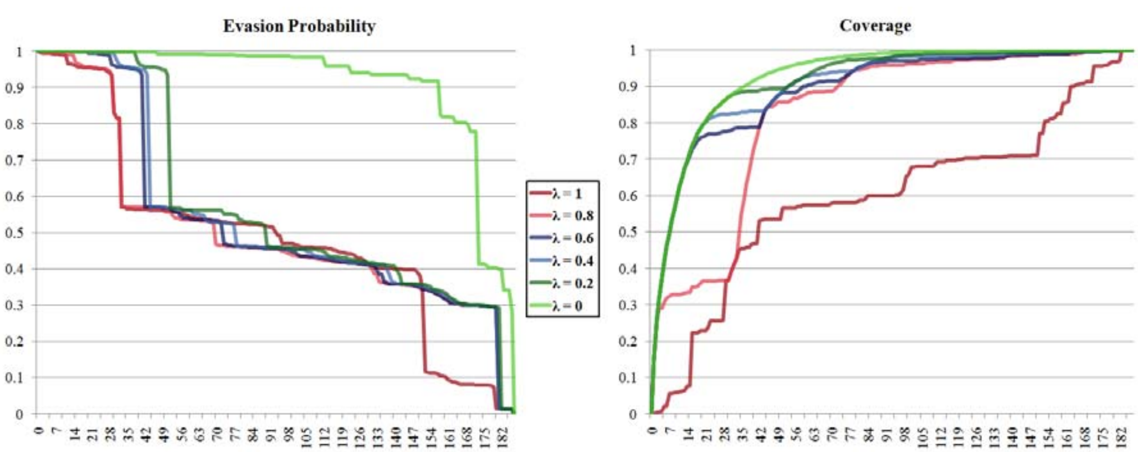

Figure 5.6: Difference in evasion probabilities and coverage between nested solutions for adversarial model, varying λ.

In the adversarial model the differences in performance against the volume smuggler and evasive smuggler are greater for varying values of λ. Whatever geographic clustering is present in this case is far less robust than in the probabilistic case, with POEs from different regions moving up and down on the priority list more for small changes in λ. Our base case with $\lambda = 0.8$, which still represents a reasonable compromise in attention paid to the two objectives, performs comparatively worse against both the optimal strategy for thwarting the evasive smuggler ($\lambda = 1$) and the optimal strategy for thwarting the volume smuggler ($\lambda = 0$) than the corresponding strategy in the probabilistic case (see Table 5.2).

	λ = 1	λ = 0.8	λ = 0.6	λ = 0.4	λ = 0.2	λ = 0
Average Difference in Evasion Probability	-7.0%	0%	+4.5%	+6.6%	+22.0%	+177.7%
Average Difference in Coverage	-30.1%	0%	+16.8%	+18.9%	+20.5%	+21.8%

Table 5.2: Adversarial model nested solution performance, varying λ.

5.3. COMPARING PROBABILISTIC AND ADVERSARIAL MODELS

The two sets of results presented above represent the effectiveness of their respective prioritizations in the context of the assumptions about the characteristics of the smuggler (probabilistic or adversarial). Therefore, the graphs demonstrating decreases in evasion probabilities cannot be compared one to one. The solutions given by neither scenario are absolutely “better” than the solutions given by the other. They are only better if smuggler threats act in the prescribed manner. Thus, we have two competing approaches, for two different assumptions. The remainder of this article focuses on the probabilistic model. This model is less susceptible to changes in origin, and can therefore better approximate the real-world threat with a limited list of origins. Since the adversarial smuggler model solutions are strongly affected by our choice of origins, it is better suited to a scenario where we know of a specific threat and are looking to respond to that threat. In other words, the probabilistic model is applicable in a passive setting, while the adversarial model is more appropriate in an active setting, for example, the emergency deployment of resources in the face of a known threat.

6. Sensitivity analysis

Apart from λ, the parameters described in Section 3.2 all influence the indigenous evasion probabilities in the network. This being the case, it is possible that the values we select for these parameters affect the outcomes of our solutions. This is undesirable, as we would like that the solutions we recommend to be robust to modest changes in these parameters. Below we perform sensitivity analyses on these parameters to determine whether this is the case.

6.1. CHANGING DETECTOR RELIABILITY

In the base case we assume that detectors are perfectly reliable. That is, any threatening amount of nuclear material will set off the detectors and that smuggler would be caught. However, this assumption is not realistic. A smuggler can use various means to decrease the risk of setting off the detectors, e.g., shielding the nuclear material in a lead enclosure. Increasing the value of the parameters q_k accounts for this. In our sensitivity analysis, we vary q_k uniformly across all ports of entry k.

6.1.1. Increasing q_k

Increasing q_k decreases the detection probability with a detector in place at port of entry k to $1 - q_k$. We observe almost no changes in the nested solution priority list (see Figure 6.1). Specifically, the priority list structure of securing sea ports first, then the U.S. border with Mexico, and finally that with Canada, remains unchanged for all of the values of q considered. This is a positive result, as it indicates that our priority list for securing POEs does not depend on the detectors' reliability, at least up to a reasonable point. However, it is important to note that despite this consistency in the priority list, the overall evasion probability grows because there is still a chance that smugglers can go through a secured POE undetected.

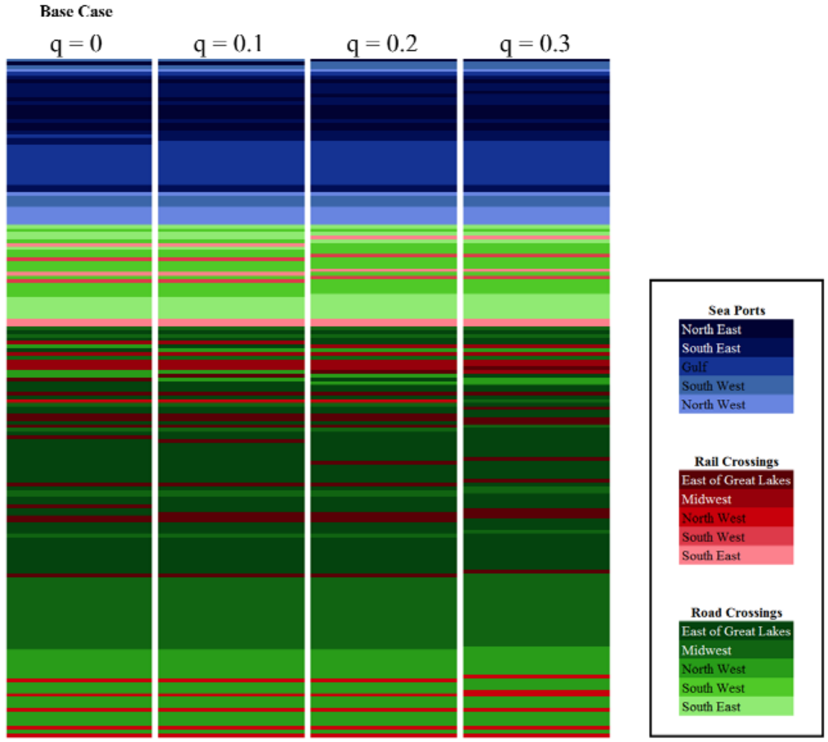

Figure 6.1: Nested solution for different values of *q*.

6.2. CHANGING BORDER CROSSING EVASION PROBABILITIES

In our model, border crossing evasion probabilities represent the evasion probability that a smuggler faces when entering the United States at a POE with no detector installed. In our base case, these are different for the different modes of transportation. As discussed in Section 4.1, we use the network topology from the LANL PATRIOT database in calculating evasion probabilities. In our analysis, most network arcs have an evasion probability greater than 0.99, while border crossings have a lower evasion probability, accounting for the special attention paid by customs and border patrol officers at these locations. We assign different evasion probabilities to the different modes of transportation to represent what we perceive to be the extent and diligence of inspections at POEs of each mode. As stated in Section 5.1.1 and Section 5.2.1, in our base cases the border crossing evasion probabilities for the different modes of transportation are as follows: 0.65 for sea, 0.75 for land, and 0.85 for rail. These parameter values were chosen to represent our belief that, in the absence of detectors, a smuggler has the greatest chance of being caught entering the country by sea and is least likely to be caught if they come by rail, with land being somewhere between the two. However, realizing that these assumptions may have an undue influence on our solutions, we perform sensitivity analysis on these parameters to see what effect, if any, their values have on the nested solution priority list.

6.2.1. Less differentiation

The first alternative we examine preserves the belief that indigenous evasion probabilities are different for different transportation modes, but with less differentiation. We test how the solution changes if border crossing reliabilities are set to 0.7 for sea, 0.75 for road, and 0.8 for rail. The priority list for this case does not change significantly from the base case (see Figure 6.2). Sea ports remain the top priority, and the order in which to secure them does not change at all. And as before, the Mexican border comes next, and the Canadian border last. Within these groups, rail crossings fall in priority somewhat, a predictable result given that a smuggler's evasion probability when going through a rail POE is now lower than in the base case. Importantly though, having less differentiation between border crossing reliabilities does not impact the geographic clustering in our solution.

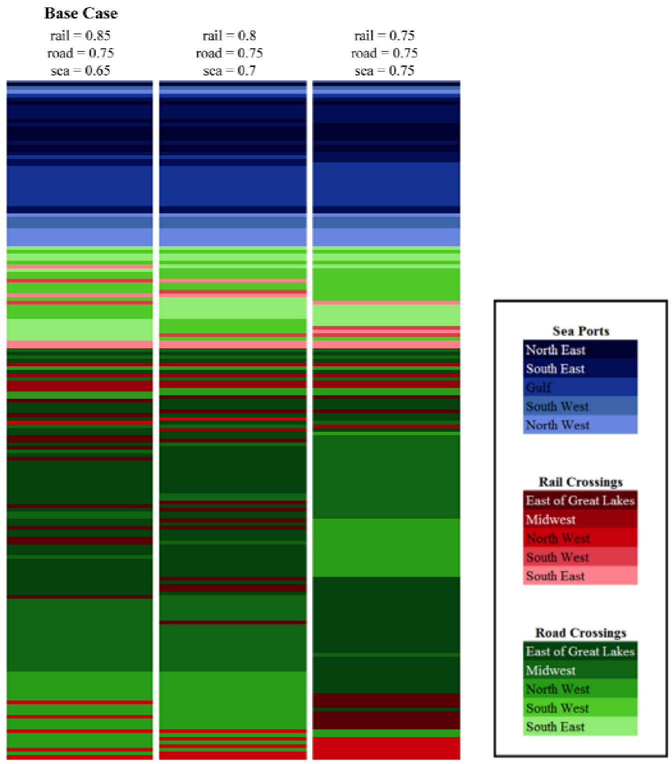

Figure 6.2: Nested solution for different border crossing reliabilities across modes of transportation.

6.2.2. All equal

We also examine what would happen to our priority ranking of POEs in the event that there is no difference in evasion probabilities for different modes. In the smuggler's eyes, this makes sea ports an even more attractive alternative than before and, as we would assume, they remain at the top of the priority list (see Figure 6.2). Meanwhile, rail POEs are now even less attractive to a smuggler. Correspondingly, we see some rail POEs slide further down priority list. Again though, the structure of the priority list remains unchanged from the base case, with sea ports being a top priority, then the Mexican border, and finally Canada. This stability is reassuring, as it indicates that our solution is not excessively sensitive to assumptions we make regarding indigenous detection probabilities at border crossings.

6.2.3. Decreasing sea port priority

The persistent high ranking of sea ports on the priority list under various assumptions begs a question: under what conditions would sea ports no longer be our first concern? Since there is no real chance of a smuggler getting caught during the actual trip by sea, it seems that decreasing the evasion probability on sea arcs makes little sense. What we could change, however, is the evasion probability at sea POEs. We want to find out how low the evasion probability of entering the United States by sea has to be so that sea ports are no longer the top priority. Another way of thinking about this is that we want to find out how good indigenous law enforcement at sea ports has to be to make installing detectors somewhere else a better use of resources.

To this end, we run the model varying the border crossing evasion probability for sea POEs (see Figure 6.3). We see that sea ports remain at the top of the priority list for sea border crossing evasion probability values as low as 0.525. Sea ports only fall below the Mexican border in the ranking when this value decreases to 0.5. Even then, some sea ports remain at the top of the priority list, due to the high volume of cargo they handle. What this reveals is that indigenous law enforcement at sea ports would have to be good enough to catch attempts to smuggle nuclear material with a probability of around 1/2 for sea ports to not be the first place where we install detectors.

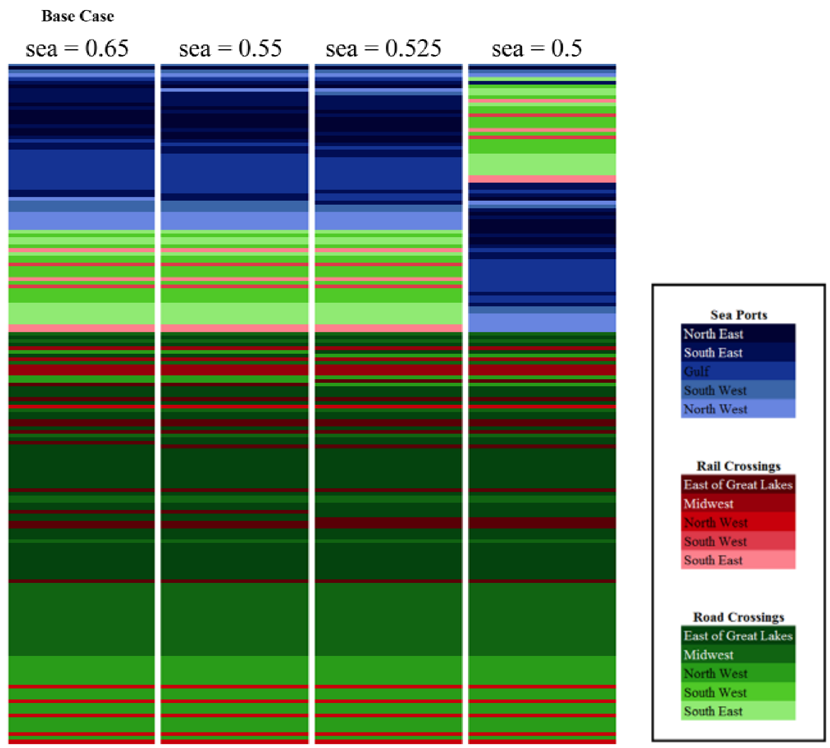

Figure 6.3: Nested solution for different sea border crossing reliabilities.

6.3. CHANGING FIXED RATES

The final set of parameters which we use to modify the intrinsic characteristics of the network is the fixed rate penalties on arcs. As discussed in Section 3.2, these fixed rates are to account for the fact that, on certain modes of transportation, a smuggler's probability of getting caught is impacted by the length of his trip. For example, the longer a smuggler drives on a highway, the more likely they are to get stopped and caught by indigenous law enforcement, simply due to increased exposure. We initially consider these in our model to address and fix illogical smuggler behavior. In our base case, the fixed rates for travel on different network modes are as follows: $\alpha_{sea} = 0$, $\alpha_{road} = 0.00008$ and $\alpha_{rail} = 0.00033334$. Below we discuss the effects of changing these fixed rates.

6.3.1. Decreasing fixed rate for rail

First, we consider how our priority list might change if the fixed rate for rail is in fact lower than what we assume. To do so, we set α_{rail} (the fixed rate for rail travel) to 0.000165, about half of the initial value, while holding everything else constant. This makes rail a relatively more attractive mode of transportation. For example, traveling the 1500km from Chihuahua, Mexico to Los Angeles, CA by rail now decreases evasion probability by a factor of 0.781 as opposed to the 0.607 we would see with the original value of α_{rail}. Rail is now preferred to road for crossing the border in some cases, but road remains the more desirable mode of transportation otherwise. Predictably, some rail POEs rise higher in the priority list, but not to the extent that they change the geographic clustering of the priority list (see Figure 6.4).

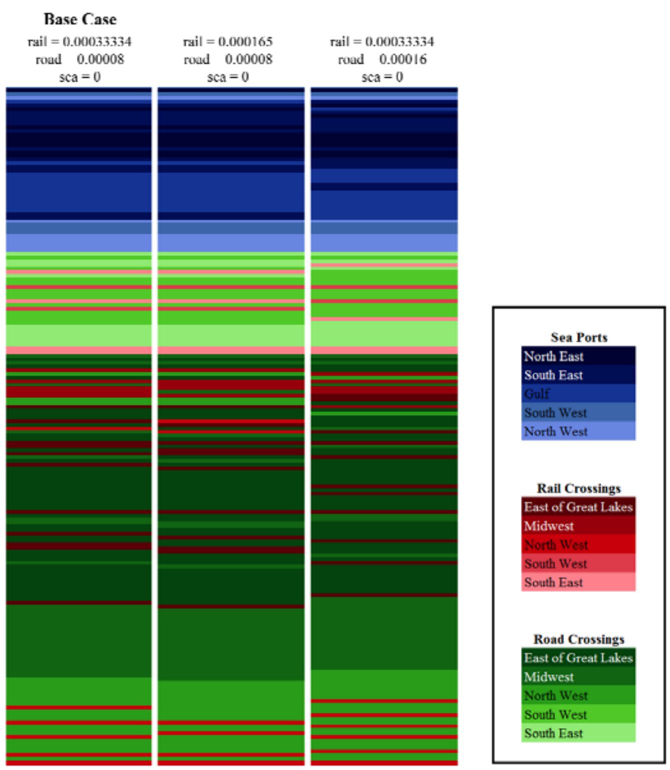

Figure 6.4: Nested solution for different arc fixed rates across modes of transportation.

6.3.2. Increasing fixed rate for road

We also examine the effect of increasing α_{road}, the fixed rate penalty on road travel. This parameter value is doubled, to 0.00016. The effect of this change is to make travel by road relatively less attractive to a smuggler. The 2500km trip by road from Winnipeg, Canada to destinations on the east coast now has a penalty factor of 0.670 on evasion probability, as opposed to 0.819 with the original value of α_{road}. Again, rail is now preferred to road for crossing the border in some cases, but road remains the transportation mode of choice everywhere other than at the border. We observe some minor reshuffling in the priority list, but no significant changes (see Figure 6.4).

7. Conclusions

The goal of this article is to analyze smuggler movements along multiple transportation networks and paths into the United States to determine the best port of entry locations at which to deploy nuclear detectors. The optimal solutions of the network interdiction model provide insight into this problem, while the nested solutions give an implementable ranked priority list of detector locations. Various models of smuggler behavior are presented and analyzed, along with analysis of solution sensitivity to parameter values. Some important takeaways are presented below.

7.1. What the model reveals

Our analysis reveals that the optimal placement of detectors given depends on the particular model of smuggler behavior used. Results in the probabilistic smuggler scenario are significantly different to those for the adversarial smuggler. This shows us that there is no one foolproof solution to the practical problem of securing the United States' borders and that the choice of strategy is contingent on our beliefs as to how a smuggler acts. This should not be discouraging though, as the different approaches can be reconciled to good effect (for example, the competing objectives of thwarting the evasive and volume smugglers). The priority list generated by the base case probabilistic model provides a logical, sensible approach to securing our borders.

One very real and practical insight garnered from analyzing the problem is that there are significant steps that can be taken to secure ports of entry into the country without even installing detectors. Specifically, the vulnerability of the Canadian border could be greatly reduced by simply closing or consolidating some ports of entry. In the case of Maine, for example, we have 23 commercial road ports of entry, many of which see minimal traffic and are in very close proximity to each other. Shutting down some or all of these very low volume ports of entry would decrease the number of potential smuggler routes into the country, and barely affect freight traffic.

7.2. Summary of Effects of Varying Parameters

The sensitivity analyses performed in this article reveal that the effects of varying parameter values (other than λ) are negligible. When we vary q, border crossing reliabilities and fixed rates, the priority list of ports of entry does not change in a significant way. The values assigned to these parameters, specifically in the base case, represent assumptions that we make with regards to the network that a smuggler travels on. Thus, this stability is reassuring, in terms of the robustness of the given solutions, as it indicates that even if our assumptions are not entirely correct, this should not invalidate our results.

7.3. Further Research and Model Amendments

While this article strives to present a comprehensive model and interdiction strategy, there are further areas of interest that can, and should, be explored in the future. For one, we currently only consider commercial ports of entry, assuming that a smuggler would make use of commercial routes in their attempts to get nuclear materials into the U.S. Expanding this to include all ports of entry, and even illegal paths into the country, would lead to greater insights and a more complete picture of the real problem faced by the interdictor.

The model could also be expanded to analyze scenarios where there is more than one line of defense (i.e., detectors can be installed in places other than U.S. ports of entry). This is discussed in Morton et al. [8] and Pan and Morton [12], but extensive analysis of these models has not been performed as yet.

Perhaps most significantly though, in its current conception, our model has one very unrealistic assumption: the budget value *b* represents the number of sites that can have detectors installed, not taking into account the actual cost of doing so. That is, we consider the cost of securing a large sea port such as the one in Los Angeles, CA to be equivalent to that of installing a detector at the single lane road port of entry in Monticello, ME. Obviously, this is not actually the case. Factoring in the monetary cost of securing different ports of entry could have a serious impact on our solutions, given the limited resources faced by the interdictor, and is something that should be considered in future research.

Appendix

All of the ports of entry into the United States used in our analysis are presented below, grouped by mode.

Rail ports of entry

Mexican border

1. Brownsville, TX
2. Laredo, TX
3. Eagle Pass, TX
4. El Paso, TX
5. Nogales, AZ
6. Calexico East, CA
7. Otay Mesa/San Ysidro, CA

Canadian border

8. Calais, ME
9. Vanceboro, ME
10. Van Buren, ME
11. Jackman, ME
12. Norton, VT
13. Richford, VT
14. Highgate Springs, VT
15. Champlain/Rouses Pt., NY
16. Trout River/Fort Covington/Chateaugay, NY
17. Buffalo/Niagara Falls, NY
18. Port Huron, MI
19. Detroit, MI
20. Sault Ste. Marie, MI
21. International Falls, MN
22. Pembina, ND
23. Portal, ND
24. Sweetgrass, MT
25. Eastport, ID
26. Boundary, WA

27. Laurier, WA
28. Sumas, WA
29. Blaine, WA

ROAD PORTS OF ENTRY

Mexican border

1. Brownsville, TX (2 crossings)
2. Progreso, TX
3. Hidalgo/Pharr, TX
4. Rio Grande City. TX
5. Roma, TX
6. Laredo, TX (2 crossings)
7. Eagle Pass, TX
8. Del Rio, TX
9. Presidio, TX
10. El Paso, TX (2 crossings)
11. Santa Teresa, NM
12. Columbus, NM
13. Douglas, AZ
14. Naco, AZ
15. Nogales. AZ
16. Sasabe, AZ
17. San Luis, AZ (2 crossings)
18. Andrade, CA
19. Calexico East, CA
20. Tecate, CA
21. Otay Mesa, CA

Canadian border

22. Lubec, ME
23. Calais, ME
24. Vanceboro, ME
25. Forest City, ME
26. Orient, ME
27. Houlton, ME
28. Monticello, ME
29. Bridgewater, ME

30. Easton, ME
31. Hamlin, ME
32. Fort Fairfield, ME
33. Limestone, ME
34. Van Buren, ME
35. Madawaska, ME
36. Fort Kent, ME
37. Estcourt Station, ME
38. Saint Pamphile, ME
39. Saint Juste, ME
40. Somerset County, ME (2 crossings)
41. Jackman, ME
42. Coburn Gore, ME
43. Pittsburg, NH
44. Beecher Falls, VT
45. Canaan, VT
46. Norton, VT
47. Derby Line, VT
48. Richford, VT (3 crossings)
49. Morses Line, VT
50. Highgate Springs, VT
51. Champlain/Rouses Pt., NY (3 crossings)
52. Mooers, NY
53. Cannon Corners, NY
54. Churrubusco/Clinton, NY
55. Chateaugay, NY
56. Jamieson Line, NY
57. Trout River, NY
58. Fort Covington, NY
59. Massena, NY
60. Ogdensburg, NY
61. Alexandria Bay/Cape Vincent, NY
62. Buffalo/Niagara Falls, NY (2 crossings)
63. Port Huron, MI
64. Detroit, MI (2 crossings)
65. Sault Ste. Marie, MI
66. Grand Portage, MN
67. International Falls, MN

68. Baudette, MN
69. Warroad, MN
70. Roseau, MN
71. Pinecreek, MN
72. Lancaster, MN
73. Pembina, ND
74. Neche, ND
75. Walhalla, ND
76. Maida, ND
77. Hannah, ND
78. Sarles, ND
79. Hansboro, ND
80. St. John, ND
81. Dunseith, ND
82. Carbury, ND
83. Westhope, ND
84. Antler, ND
85. Sherwood, ND
86. Northgate, ND
87. Portal, ND
88. Noonan, ND
89. Ambrose, ND
90. Fortuna, ND
91. Raymond, MT
92. Whitetail, MT
93. Scobey, MT
94. Opheim, MT
95. Morgan, MT
96. Turner, MT
97. Wildhorse, MT
98. Whitlash, MT
99. Sweetgrass, MT
100. Del Bonita, MT
101. Piegan, MT (2 crossings)
102. Roosville, MT
103. Eastport, ID
104. Porthill, ID
105. Metaline Falls, WA

106. Boundary, WA
107. Frontier, WA
108. Laurier, WA
109. Oroville, WA
110. Sumas, WA
111. Lynden, WA
112. Blaine, WA

SEA PORTS OF ENTRY

East coast

1. Chicago, IL
2. Portsmouth, NH
3. Boston, MA
4. New York, NY
5. Newark, NJ
6. Philadelphia, PA
7. Chester, PA
8. Wilmington, DE
9. Baltimore, MD
10. Richmond/Petersburg, VA
11. Newport News, VA
12. Norfolk, VA
13. Wilmington, NC
14. Charleston, SC
15. Savannah, GA
16. Fernandina Beach, FL
17. Jacksonville, FL
18. Fort Pierce, FL
19. West Palm Beach, FL
20. Port Everglades, FL
21. Miami, FL

Gulf of Mexico

22. Port Manatee, FL
23. Tampa, FL
24. Panama City, FL
25. Mobile, AL

26. Gulfport, MS
27. New Orleans, LA
28. Gramercy, LA
29. Lake Charles, LA
30. Beaumont, TX
31. Galveston, TX
32. Houston, TX
33. Freeport, TX
34. Corpus Christi, TX

West coast

35. Port Townsend, WA
36. Everett, WA
37. Seattle, WA
38. Tacoma, WA
39. Longview, WA
40. Vancouver, WA
41. Portland, OR
42. Oakland, CA
43. Port Hueneme, CA
44. Long Beach, CA
45. Los Angeles, CA
46. San Diego, CA

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